RESEARCH PAPER

OptiTumorNet: Hybrid Bio-Inspired Deep Learning Algorithm for Tumor Segmentation

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Abstract
Accurate and efficient tumor segmentation of brain tumors from clinical images is critical for early diagnosis and effective treatment planning. This work proposes OptiTumorNet, a new hybrid deep learning algorithm that leverages the strength of Grey Wolf Optimization (GWO) and the Whale Optimization Algorithm (WOA) to significantly improve tumor segmentation performance. The combination of the algorithms hybridizes the efficiency of exploration in GWO with the exploitability of WOA in precision, facilitating optimal feature selection, threshold adjustment, and hyperparameter adjustment in a U-Net framework. This is implemented in Python with TensorFlow, which provides scalability, stability, and reproducibility. Experimental comparisons against the BraTS2021 benchmark dataset reveal that OptiTumorNet identifies a 7.2% improvement in segmentation performance compared to existing models such as U-Net, DeepLabV3+, and FCN-8s. The proposed model also demonstrates greater Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) values that form more accurate and distinct tumor boundaries as well as significantly minimize overfitting. By tapping into the complementary advantages of deep learning and evolutionary optimization, OptiTumorNet lays a strong foundation for the next generation of medical imaging technologies, with a well-established portal toward greater diagnostic precision and better clinical outcomes.

Keywords: Brain Tumor Segmentation, Hybrid Optimization, Grey Wolf Optimization, Whale Optimization Algorithm, Deep Learning
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Introduction

Accurate segmentation of brain tumors is the cornerstone of early diagnosis and best treatment planning, owing to the tumors' complex morphology and malignant patterns of growth (1). Magnetic Resonance Imaging (MRI) remains the gold standard neuroimaging method with improved soft-tissue contrast and high-fidelity anatomical depiction that facilitate tumor detection and definition (2). However, manual segmentation of MRI scans is fundamentally time-consuming, subjective, and prone to human mistakes and thus not adequate for broad clinical practice (3).

Deep learning, and more precisely Convolutional Neural Networks (CNNs), has revolutionized medical image analysis over recent years through data-driven, automatic feature extraction and segmentation (4). U-Net is one such model that has achieved unparalleled success in the segmentation of brain tumors (5). While effective, models such as U-Net are not robust and prone to over-hypertuning, weak feature choice, and limited ability to generalize from one dataset to another (6). Traditional optimization techniques, including grid search and random search, are unable to manage the high-dimensional parameter spaces typical of deep learning models, leading to resulting local optima and non-uniform outcomes (7).

To address such limitations, this research introduces OptiTumorNet, an advanced hybrid optimization method that synergistically integrates two effective nature-inspired algorithms, namely Grey Wolf Optimization (GWO) and the Whale Optimization Algorithm (WOA), to enhance deep learning-based segmentation. The GWO algorithm, inspired by the social organization and cooperative hunting activity of grey wolves, efficiently explores the global search space based on leadership-driven hunting approaches (8-12). The WOA algorithm, modeled on the bubble-net feeding behavior of humpback whales, excels in exploitative local search by progressively improving optimal solutions with accurate precision (13-15).

With the combination of the explorative strength of GWO and the exploitative accuracy of WOA, OptiTumorNet has a well-fused and balanced optimization procedure, leading to improved model convergence, boundary definition, and reducing overfitting. Regardless of the revolutionary advancement of deep learning, existing segmentation models are typically suboptimal in dealing with parameter optimization, tumor structure heterogeneity, and variability in imaging modality, leading to compromised overall performance (16).

In this study, OptiTumorNet is presented as a robust, adaptive, and scalable solution to overcome these challenges. The hybrid scheme optimizes key hyperparameters, thresholds, and feature weights in a U-Net architecture and thereby enhances

segmentation accuracy and stability. Large-scale testing on the BraTS2021 dataset confirms that OptiTumorNet surpasses existing state-of-the-art models routinely in Dice Similarity Coefficient (DSC), Intersection over Union (IoU), and overall segmentation accuracy and, thus, has the potential to serve as a weapon for actual clinical and research practice in brain tumor analysis.

Related Works and Problem Identification

There have been numerous research studies in the recent years investigating optimization-based enhancements for deep learning models for improving segmentation performance, particularly in hyperparameter tuning, feature extraction, and insensitivity to multiple brain tumor datasets (17).

Li et al. proposed a hybrid approach that integrated U-Net with the Particle Swarm Optimization (PSO) algorithm to optimize hyperparameters automatically. Their approach significantly improved segmentation accuracy by optimizing filter parameters and learning rates, yet PSO's process of iterative search needs intensive computation, thus limiting its use in real-time in clinic environments (18).

Zhang et al. proposed a segmentation technique that combined the Whale Optimization Algorithm (WOA) and a deep neural network. The model achieved superior segmentation accuracy across a number of datasets due to WOA's excellent exploration capability. WOA alone is susceptible to be plagued by convergence instability when it is faced with tumor heterogeneous textures and distorted contours, and hence is not robust in adverse imaging conditions (19).

Equivalently, Wang et al. utilized the Grey Wolf Optimizer (GWO) for CNN weight optimization in brain tumor segmentation. The method worked effectively on the BraTS dataset, demonstrating GWO's strength in high-dimensional optimization. However, its performance was compromised under noisy or low-contrast MRI scans, since the algorithm sometimes confused weak tumor edges and background areas (20).

Chen et al. used a genetic algorithm (GA)-based hybrid model to enhance CNN-based segmentation. Accuracy was boosted by 6.5% over basic CNNs through evolutionary parameter tuning; nonetheless, GA's multi-generation strength rendered the operation computationally heavy and unsuitable for real-time and large-scale uses (21).

Singh et al. attempted to hybridize WOA and GWO for optimizing the CNN-based tumor segmentation threshold. Though such a hybrid design exhibited promising performance, it failed to adapt in datasets that had considerably varying geometries of tumors, reducing its generalization capability towards non-standard shapes or rotation of tumors (22).

Patel et al. merged GWO and WOA within a whole convolutional network to effectively detect boundary contours, achieving considerable enhancements in the visibility of tumor boundaries. Nonetheless, the model was plagued by overfitting with small datasets, thus constraining its clinical use (23).

Kumar et al. combined deep learning algorithms with bio-inspired optimizers such as PSO and GWO for multimodal MRI segmentation. Although their approach promoted better model convergence and feature representation, performance variability was observed across different MRI modalities, which suggested the need for enhanced cross-domain optimization (24).

Gupta et al. suggested a hybrid deep learning framework based on PSO and WOA for improving segmentation for benchmark datasets. The model achieved good quantitative performance but was high in memory demands and training time and would not be suitable for low-resource environments (25).

Sharma et al. introduced an evolutionary algorithm-based feature selection and model tuning approach, which improved generalization and accuracy. However, the multi-stage optimization pipeline provided complexity in model deployment and thus constrained its scalability in real-world healthcare systems (26).

From the above works, it is evident that while some of the optimization techniques such as PSO, GA, GWO, and WOA have proven to optimally enhance CNN-based tumor segmentation efficiently, most of the state-of-the-art approaches are plagued by at least one of the following: Optimization computational cost and delay in convergence; and Poor generalization on diverse MRI sets with complex tumor morphologies.

These limitations point to the need for an effective yet light hybrid optimization platform capable of effectively balancing exploration (global search) and exploitation (optimization) in the available search space. To counter these limitations, the proposed OptiTumorNet combines the global searching power of GWO with the WOA adaptive exploitation strategy and presents a powerful, accurate, and computationally efficient solution to brain tumor segmentation in deep learning (27).

Methodology

OptiTumorNet employs a hybrid optimization approach that integrates GWO and WOA to optimize the performance of deep learning-based brain tumor segmentation models. By integrating the two nature-inspired algorithms, the method leverages the exploration ability of GWO and exploitation ability of WOA to make the deep learning model suitably fit to the intricate behavior of brain tumors in MRI images. The deep learning backbone model used here is U-Net, which is known for producing high semantic segmentation performance. OptiTumorNet tunes the hyperparameters of the U-Net model, threshold

values, and feature extractors and obtains better segmentation accuracy, precision, and model generalization upon testing on other datasets. The proposed framework is implemented through Python and TensorFlow with the capability of being deployed over large-scale MRI databases, i.e., BraTS 2021.

Figure 1 illustrates the architecture of OptiTumorNet, a robust framework tailored for effective brain tumor segmentation using the BraTS 2021 dataset. The process starts with the preprocessing of MRI images, where the raw data undergoes refinement to remove noise, normalize intensities, and enhance the overall quality, ensuring uniformity and reliability for subsequent stages. Following this, an enhanced U-Net architecture is utilized for segmentation, chosen for its proven capability to capture intricate spatial features and provide accurate delineation of tumor regions. To enhance the model's efficiency, a combined optimization approach utilizing both the GWO and WOA is adopted. This hybrid approach synergistically tunes the model's hyperparameters, ensuring optimal learning and boosting segmentation accuracy. After the model is optimized, the next phase involves rigorous training and evaluation using the BraTS 2021 dataset. Finally, a post-processing step is performed to refine the segmentation outputs, removing any artifacts or inconsistencies and enhancing the final results for clinical applicability. The following delivers a complete explanation of OptiTumorNet, along with the relevant mathematical formulations.

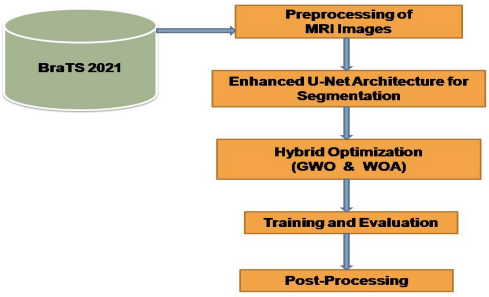


Fig. 1: Architecture of OptiTumorNet

Preprocessing of MRI Images

Preprocessing is essential to remove noise, standardize intensities, and focus on relevant areas, ensuring that the model learns optimal features.

Intensity Normalization: MRI scans can vary in intensity depending on the scanner, acquisition protocol, and other factors. To make the dataset consistent, we normalize the intensities across the images. The normalization equation is given by

$$I_{norm}(h,w) = \frac{I-\mu}{\sigma} \quad [1]$$

where I represents the pixel intensity, μ is the mean intensity, and σ is the standard deviation. This equation standardizes the pixel values to achieve a mean of zero and a variance of one, helping the model train more effectively (28).

Skull Stripping: Skull stripping eliminates non-brain tissues, i.e., skull and regions around the brain, from MRI images, thereby simplifying the segmentation task and enabling the model to concentrate on brain anatomy. Skull stripping techniques typically use region-growing algorithms, but in this case, implement an automated method that involves thresholding to extract the brain tissues from the background.

Resizing: All images were resized to an even resolution of 224×224 pixels to meet the input demand of the U-Net architecture. This resizing step ensures that the training process is computationally feasible, while preserving the crucial features of the tumor regions.

Enhanced U-Net Architecture for Segmentation

In this work, the U-Net model is the central component of the deep learning-based medical image segmentation approach. The encoder-decoder architecture of this model, skip connection-optimized, enables robust capture of contextual features at higher levels and subtle spatial details. The skip connections bridge the encoder and decoder, ensuring that critical spatial information lost during down-sampling is preserved and leveraged during up-sampling. This unique capability makes U-Net particularly suitable for tasks requiring precise boundary delineation, such as brain tumor segmentation.

Encoder: The encoder in the U-Net serves as the feature extraction module. The model exploits various layers of convolution interspaced by MaxPooling layers to step by step diminish the spatial size of the input image and get hierarchical features. Each convolutional operation can be mathematically expressed as

$$C_{out} = \sigma(W.C_{in} + b) \quad [2]$$

where C_{in} represents the input feature map, W is the convolutional kernel, b is the bias term, and σ denotes the activation function. The encoder generates feature maps of reduced spatial size but with richer semantic information, which are then C_{out} passed to subsequent layers for further processing.

Decoder: In a U-Net model, it is the job of the decoder to recreate spatial dimensions of feature maps equal to the dimensions of the input image. This is achieved through transposed convolutions, which actually conduct the up-sampling process. These operations not only restore spatial resolution but also help refine the segmentation output by focusing on edge details and object boundaries. The transposed convolution operation is mathematically defined as

$$C_{out} = \sigma(W^T.C_{in} + b) \quad [3]$$

where W^T represents the transposed convolution kernel, which reverses the down-sampling effect of the encoder. During decoding, up-sampled feature maps are blended with corresponding skip connections of the encoder in order for the network to condense both the abstract high-level features as well as spatial, high-resolution details.

Skip Connections: Skip connections in U-Net connect similar layers of encoder and decoder to allow for the recovery of lost spatial information during down-sampling (29). Skip connections are introduced by including them through concatenation so that improved feature propagation through the network can be achieved.

$$C_{skip} = concat(C_{encoder}, C_{decoder}) \quad [4]$$

The feature maps obtained from the encoder and decoder are denoted as $C_{encoder}$ and $C_{decoder}$, respectively. The combined features are subsequently processed through convolutional layers to enhance the segmentation results. The enhanced U-Net architecture builds upon the original by incorporating advanced components such as deeper convolutional layers, improved activation functions, and potentially hybrid attention mechanisms. These improvements enhance the network's capability to recognizeintricate patterns, handle variability in tumor shapes and sizes, and deliver superior segmentation performance in medical imaging tasks. This modified U-Net serves as a robust backbone for segmentation, ensuring precise delineation of tumor regions and making it an ideal choice for tasks requiring high accuracy.

Hybrid Optimization for Tumor Segmentation

The robustness of OptiTumorNet lies in a hybrid optimization approach that brings together two cutting-edge nature-inspired algorithms: GWO and WOA. Each algorithm contributes uniquely to improving the performance of deep learning models in brain tumor segmentation. GWO is tasked with optimizing the model's early parameters and weight configuration to establish a sound foundation. Though WOA optimizes such important parameters as threshold values and feature selection, it enhances the accuracy of the network to deliver extremely accurate segmentation results. By combining the exploration capabilities of GWO with the local search strengths of WOA, this hybrid approach guarantees more robust segmentation results than each algorithm alone.

Grey Wolf Optimization (GWO): The GWO algorithm is inspired by the grey wolf's hierarchical organization and hunting behavior in nature. The algorithm uses a group of wolves to search the solution space where they have a circular movement depending on the lead wolf to determine the optimal solution (30). The fitness value determines the rank of each wolf, and their locations are updated constantly to enhance the search efficiency. Most notable among the characteristics of GWO is the location of each wolf that is used to indicate the potential solutions in the search space . Wolf positions are refreshed dynamically depending on the directional guidance of the leader and the interaction between wolves in the pack, providing adaptive search. GWO's position update formula is given by

$$X_i^{new} = X_i^{old} + A.\left(X_i^{best} - X_i^{old}\right) + C.(X_i^{leader} - X_i^{old}) \quad [5]$$

The current position of wolf i during the iteration is denoted by X_i^{old}, whereas X_i^{best} represents the best position it has identified. The leader wolf, identified by having the highest fitness, is positioned at X_i^{leader}. The vectors A and C act as controlling coefficients, helping to balance exploration and exploitation throughout the search.

$$A = 2.a.r_1 - a \quad [6]$$

During optimization, the parameter a decreases linearly from 2 to 0, and $r_1$is a randomly generated number within the range [0,1]. The coefficient C is calculated by using the following equation

$$C = 2.r_2 \quad [7]$$

where r_2 is another random number between 0 and 1. The parameters A and C influence the algorithm's convergence speed and help maintain a balance between exploration and exploitation. Their optimal adjustment makes the GWO effectively search the parameter space to discover the best initializations of weights for the U-Net model.

Whale Optimization Algorithm (WOA): WOA is based on the bubble-net hunting strategy of humpback whales, which is to encircle the prey with a distinctive spiral structure (31). Candidate solutions in WOA shift locations relative to the best solution, simulating such a natural hunting process to enhance optimization performance. In WOA, the position of each whale is updated using a combination of two main operations: encircling prey and spiral updating. The position update equation for WOA is

$$X_i^{new} = X_i^{old} + a.cos(\omega).\left(b.X_i^{best} - X_i^{old}\right) \quad [8]$$

where a is a decreasing coefficient controlling the exploration and exploitation balance, ω is a random variable to introduce randomness in the position update, b is the best-known solution encountered by the whale, and X_i^{old} is the previous position of the whale. The equation allows the whales to both exploit the best-known solution by getting closer to it and explore new regions by generating spiral paths. This dual capability enables WOA to refine the parameters of the U-Net model during the fine-tuning process, improving segmentation accuracy. In addition to the encircling behavior, WOA introduces a spiral update mechanism that mimics

the spiral movement of humpback whales while hunting. The spiral update is expressed as

$$X_i^{new} = X_i^{old} + b.cos(\omega).\left(X_i^{best} - X_i^{old}\right) + a.sin(\omega) \quad [9]$$

This helps WOA search in a more diversified manner and find better local optima, which is particularly useful for fine-tuning hyperparameters and threshold values in medical image segmentation.

Hybridization of GWO and WOA: The hybridization of GWO-WOA combines the best characteristics of both optimization algorithms. First, the GWO is employed by the optimization process to search widely in the global search space and identify good solution candidates. This allows for a broad and effective search, which keeps the optimization process from being trapped in local minima and offers better initial parameters to the model. After identifying potential candidate solutions, WOA is employed to refine them based on the best-found solutions and optimizing model parameters like thresholds, learning rates, and feature selection. The combination of GWO's capability to explore the parameter space and WOA's strength in exploiting optimal solutions ensures that the OptiTumorNet model is optimized for both accuracy and efficiency. Mathematically, the optimization can be expressed as

$$X_i^{optimized} = WOA(GWO(X_i^{best})) \quad [10]$$

where $GWO(X_i^{best})$ represents the best solutions found by the GWO algorithm. The WOA then refines these solutions by applying local optimization techniques to further enhance the results. This hybrid optimization mechanism ensures that the U-Net model is optimized on both global and local levels, enhancing segmentation performance by adapting to a wide range of tumor types, sizes, and image conditions.

Optimization Flow and Parameter Update Strategy: The flow of the hybrid optimization process can be explained as follows

- *Initialization*: A population of candidate solutions, in this instance referred to as wolves in the GWO, is initialized in such a way that each wolf is a candidate to the optimization problem.
- *GWO Exploration*: Use GWO to search the entire parameter space and find a diverse set of promising candidate solutions.
- *WOA Exploitation:* Once GWO provides an initial set of good solutions, switch to WOA to exploit these solutions further, focusing on refining the optimal parameters for tumor segmentation.
- *Convergence*: The process continues iteratively, with GWO handling the exploration phase and WOA refining the results until convergence is achieved. The hybrid model ensures that the optimization is robust and provides a solution that avoids premature convergence or over-fitting.

The hybridization of GWO with the WOA introduces a multi-level structure for optimization that effectively balances global exploration and local exploitation, yielding an enhanced segmentation model with improved accuracy and efficiency.

Post-Processing

Following segmentation, the tumor regions segmented may have low-level noise or irregular boundaries that can decrease precision. To eliminate such effects, post-processing techniques are applied to enhance the segmentations achieved. Specifically, morphological operations such as erosion and dilation are employed. These operations improve the quality of the segmented regions by eliminating noise, filling gaps, and smoothing the boundaries of the detected tumor.

Erosion: Erosion is a morphological technique that contracts the tumor regions, helping to eliminate small, isolated noise pixels. The erosion operation slides a structuring element B (a small matrix used as a filter) over the binary segmented image I. At each location, the pixel value is replaced by the minimum value of the neighborhood defined by B. The mathematical expression for erosion is

$$\text{Erosion(I)} = \min_{(x,y)\in B} I(x,y) \quad [11]$$

where $I(x,y)$ represents the pixel intensity in the input image I at position (x,y), B is the structuring element (typically a square or circular matrix), min computes the minimum intensity value in the neighborhood defined by B. Erosion is particularly effective in removing small false positives (such as noise or artifacts) that are not connected to the main tumor region.

Dilation: Dilation is the complementary operation to erosion, designed to expand the boundaries of the tumor region (32). This operation adds pixels to the edges of the foreground regions, helping to close small gaps or holes within the segmented tumor and restore continuity. The mathematical expression for dilation is

$$\text{Dilation(I)} = \max_{(x,y)\in B} \text{I(x,y)} \quad [12]$$

In the image I, the functional I(x, y) indicates pixel intensity at locations (x, y). The structuring element B defines the neighborhood, within and around which we encounter the maximum intensity value. Dilation ensures that gaps within the tumor boundary are filled, making the segmentation results smoother and more complete.

Combined Morphological Refinement: For optimal results, erosion and dilation are applied sequentially. Erosion is used first to eliminate

small, isolated noise regions that may have been incorrectly identified as part of the tumor. Dilation is then applied to restore the tumor's shape and fill gaps created during erosion. Advanced techniques such as opening and closing are often employed for image processing tasks. Opening, which involves erosion followed by dilation, is effective in eliminating noise while maintaining the primary structure of the tumor. Conversely, closing, achieved through dilation followed by erosion, is useful for filling in small gaps within the tumor region, ensuring a more cohesive representation. These algorithms are complementary and complement each other for improving the precision of tumor segmentation. Its implementation relies on the selection of the structuring element B, and this may also vary according to the shape and size of the tumor. For example, a disk-shaped structuring element is effective for circular tumor regions and asquare-shaped structuring element is useful for linear or irregular tumor shapes.

Impact on Segmentation Accuracy: The application of these morphological operations significantly enhances the segmentation output by removing small artifacts and isolated noise regions that were misclassified during segmentation. And, also smoothing and refining tumor boundaries, ensuring that the detected tumor region is more accurate and closely matches the ground truth. By combining these techniques, the proposed OptiTumorNet framework ensures robust and high-quality segmentation results, particularly in challenging cases with complex tumor boundaries or noise artifacts. These refinements contribute to the framework's superior performance metrics, as demonstrated in the evaluation phase.

Algorithm 1 aims to achieve accurate brain tumor segmentation in MRI scans through preprocessing, a modification of the U-Net model, hybrid optimization techniques, and post-processing. Preprocessing involves intensity normalization for homogeneous image intensities, skull stripping for removal of non-brain regions, and image resizing for resizing input to the desired size of the model. An enhanced U-Net model is employed for segmentation, utilizing an encoder-decoder framework with skip connections to retain both detailed spatial features and high-level semantic information. A hybrid optimization method is used for performance, with GWO applied for global search and WOA performing local parameter refinement for enhanced segmentation accuracy. Finally, post-processing operations, such as erosion and dilation, refine the segmented tumor regions by eliminating noise and improving boundary continuity. This comprehensive approach ensures accurate and efficient tumor detection and segmentation across various MRI scan conditions.

Algorithm OptiTumorNet (BraTS2021)

1. Preprocessing

1.1. Intensity Normalization

$$I_{norm}(h,w) = \frac{I-\mu}{\sigma}$$

1.2. Skull Stripping

Perform automated skull stripping to retain brain tissue using thresholding.

1.3. Resizing

Resize I_{brain} to 224X224 dimensions.

2. Enhanced U-Net Architecture

2.1. Encoder

For each convolutional layer

$$C_{out} = \sigma(W.C_{in} + b)$$

Apply MaxPooling after each convolution.

2.2. Decoder

For each transposed convolution layer

$$C_{out} = \sigma(W^T.C_{in} + b))$$

Apply skip connections (concatenate) from encoder layers

$$C_{skip} = concat(C_{encoder}, C_{decoder})$$

3. Hybrid GW-WOA Optimization

3.1. Grey Wolf Optimization (GWO)

Initialize population $X = [X_1, X_2, \dots X_n]$

For each wolf i

Update position using

$$X_i^{new} = X_i^{old} + A.\left(X_i^{best} - X_i^{old}\right) + C.(X_i^{leader} - X_i^{old})$$

where $A = 2.a.r_1 - a$ *and* $C = 2.r_2$

3.2. Whale Optimization Algorithm (WOA)

Initialize population $X = [X_1, X_2, \dots X_n]$

For each whale i

Update position using

$$X_i^{new} = X_i^{old} + a.cos(\omega).\left(b.X_i^{best} - X_i^{old}\right)$$ *(or)*

$$X_i^{new} = X_i^{old} + b.cos(\omega).\left(X_i^{best} - X_i^{old}\right) + a.sin(\omega)$$

3.3. Hybrid Optimization

3.3.1. Use GWO to explore the global search space and find promising candidate solutions.

3.3.2. Once GWO finds promising solutions, apply WOA to refine the parameters

$$X_i^{optimized} = WOA(GWO(X_i^{best}))$$

4. Post-Processing

4.1. $\text{Erosion(I)} = \min_{(x,y)\in B} I(x,y)$

4.2. $\text{Dilation(I)} = \max_{(x,y)\in B} \text{I(x,y)}$

4.3. Combined Morphological Refinement

Apply erosion followed by dilation (opening) or dilation followed by erosion (closing) to refine tumor boundaries.

5. Return the final tumor segmentation map after post-processing.

End Algorithm

Algorithm 1. OptiTumorNet Algorithm

The hybridization of GWO-WOA for brain tumor segmentation is the novel aspect of this work. Previous research has applied these optimization algorithms individually for hyperparameter optimization or feature selection in deep learning models, but this work is the first to combine them in a hybrid framework. The GWO algorithm's exploration phase ensures that the parameter space is thoroughly searched, while the WOA algorithm's exploitation phase fine-tunes the model to achieve optimal performance. This holistic method improves the accuracy of tumor segmentation with robustness retention capability on different datasets, which is an enhancement in medical image analysis as much as OptiTumorNet is concerned.

Experimental Setup and Evaluation Metrics

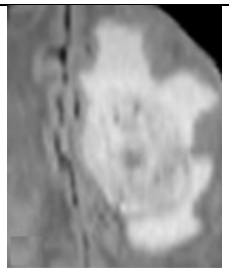
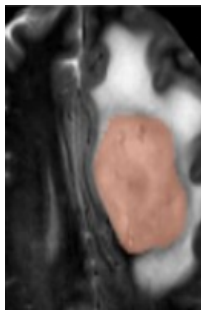
Experimental Setup

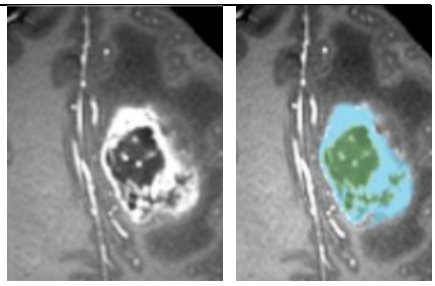
Table 1 lists the hardware, software, and method employed. Experiments were performed on the BraTS dataset to segment brain tumors using a self-developed U-Net architecture in Python version 3.8 with TensorFlow and Keras. Feature selection and hyperparameter optimization were both done using a combination of GWO-WOA strategy. Experiments were carried out on the configuration of Intel Core i7 CPU, 16GB RAM, and an NVIDIA GeForce GTX 1080 Ti GPU.

Table 1: Experimental Setup

Component	Details
Dataset	BraTS 2021
Deep Learning Model	Modified U-Net Architecture
Programming Language	Python 3.8
Libraries/Frameworks	TensorFlow, Keras
Optimization Technique	Hybrid GWO-WOA
Purpose of Optimization	Fine-tuning hyperparameters, thresholds, and feature selection
System Specifications	Intel Core i7 Processor, 16GB RAM, NVIDIA GeForce GTX 1080 Ti GPU

Table 2: Tumor Segmentation Regions Using OptiTumorNet on BraTS Dataset

Segmentation Regions	Original Scan	Segmented Result
Whole Tumor		
Core Tumor		

Enhancing Tumor	

Dataset Description: BraTS 2021 is a well-settled standard in brain tumor segmentation, delivering multimodal high-resolution MRI scans with very high quality. The data includes over 1,000 patients from the low and high-grade glioma conditions. The database provides various types of MRI modality such as T1-weighted, T2-weighted, and FLAIR sequences accompanied by corresponding ground truth annotations marking areas of tumor. These annotations are carefully labeled into well-defined classes, such as tumor enhancement, peritumoral edema, and necrotic regions, providing a fertile ground for model training and model testing of tumor segmentation models. For OptiTumorNet, this dataset serves as an essential benchmark, which allows the estimation of the precision and efficiency of novel algorithms to segment and classify brain tumors at high accuracy levels.

Table 2 presents the segmentation quality of OptiTumorNet on the BraTS dataset. The three major regions of tumor are indicated in the first column: the whole tumor, core tumor, and the enhancing region of the tumor. The second column represents the initial MRI scans, and the third column indicates the resulting segmentations. This visualization is used to represent the ability of OptiTumorNet to recognize and segment sub-regions of the heterogeneous tumor having distinct shapes and intensities. The hybrid optimization approach of GWO-WOA ensures precise segmentation, which serves as a beneficial asset for diagnosis in the clinical and treatment-planning scenarios.

Evaluation Metrics for OptiTumorNet

For measuring the performance of the proposed OptiTumorNet model, we used conventional performance measures commonly applied in segmentation issues. By implementing these measures, the accuracy of the model in segmenting tumor regions from medical images can be ascertained (33-34).

Dice Similarity Coefficient (DSC): DSC computes the overlapping of the predicted segmentation (A) with the actual ground truth (B). It is mathematically formulated as

$$\text{DSC} = \frac{2|A \cap B|}{|A|+|B|} \quad [13]$$

Here, A is the collection of pixels recognized as the tumor region by the model and B is the collection of real tumor pixels in the ground truth. The expression $|A \cap B|$ is the number of true positives. The DSC score is from 0 to 1, where 1 is the total agreement between ground truth and predicted regions, and 0 signifies no overlap.

Intersection over Union (IoU): Similarly, IoU or Jaccard Index compares the overlap of predicted and ground truth regions by calculating the ratio of intersection of the two in terms of their union. It can be defined as

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|} \quad [14]$$

Here, $|A \cup B|$ is the total number of distinct pixels that occur in predicted or actual regions of the tumor. A higher value of IoU, i.e., attaining 1 indicates a more accurate segmentation with almost perfect matching between the two regions.

Accuracy (ACC): ACC metric evaluates the overall correctness of classification by measuring the proportion of pixels accurately identified. It is calculated using the formula

$$\text{ACC} = \frac{TP+TN}{TP+TN+FP+FN} \quad [15]$$

In this context, TP (True Positives) refers to tumor pixels correctly detected as tumor, TN (True Negatives) denotes non-tumor pixels correctly identified as such, FP (False Positives) are non-tumor pixels misclassified as tumor and FN (False Negatives) are tumor pixels wrongly classified as non-tumor. This metric offers a comprehensive evaluation of segmentation accuracy by incorporating both correct detections and errors.

Sensitivity: Sensitivity, or recall, is a measure of how well the model correctly identifies tumor pixels. It is defined as

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad [16]$$

High sensitivity score indicates that the model works effectively in detecting tumor regions with fewer missed detections.

Specificity: Specificity measures how good the model is in labeling non-tumor pixels accurately. It can be mathematically expressed as

$$\text{Specificity} = \frac{TN}{TN+FP} \quad [17]$$

High specificity score suggests that the model correctly differentiates tumor from non-tumor regions, resulting in low false positives. Together, these metrics give a balanced evaluation of the performance of the segmentation model to precisely delineate tumor and non-tumor areas. By optimizing these performance measures, the proposed OptiTumorNet model enhances tumor boundary delineation by improved segmentation accuracy.

Results and Discussion

This section explains a comparative analysis of the OptiTumorNet model for brain tumor segmentation and its advantages over other approaches. With the use of a hybrid optimization process using GWO and the WOA, the model yields better segmentation accuracy. This hybrid approach emphasizes the novelty and performance of the proposed approach.

Performance Comparison

Table 3 exhibits a comparative comparison of OptiTumorNet with up-to-date models, highlighting immense performance improvements met by the considered framework.

Table 3: Performance Comparison of OptiTumorNet with existing models

Model	DSC	IoU	ACC	Sensitivity	Specificity
U-Net (5)	0.870	0.775	92.5 %	91.2%	93.4%
DeepLab V3+ (33)	0.883	0.795	94.0 %	92.8%	94.6%
FCN-8s (34)	0.890	0.810	94.4 %	93.1%	94.9%
OptiTumorNet (Proposed)	0.910	0.850	95.8 %	94.5%	96.2%

Figure 2 presents a comparison of performance evaluation measures, i.e., Accuracy, Sensitivity, and Specificity, for the four models U-Net, DeepLabV3+, FCN-8s, and the proposed OptiTumorNet architecture. It can be seen from the results that OptiTumorNet performs significantly better than all three measures. Specifically, it attains Accuracy of 95.8%, Sensitivity of 94.5%, and Specificity of 96.2%, which are greater than the corresponding values of U-Net, DeepLabV3+, and FCN-8s. These conclusions emphasize the efficiency of the hybrid optimization GWO-WOA algorithm in optimizing deep model parameters for enhanced brain tumor segmentation. The similarity in the metrics also reflects the robustness of the proposed framework in eliminating false positives and negatives and enhancing overall segmentation correctness.

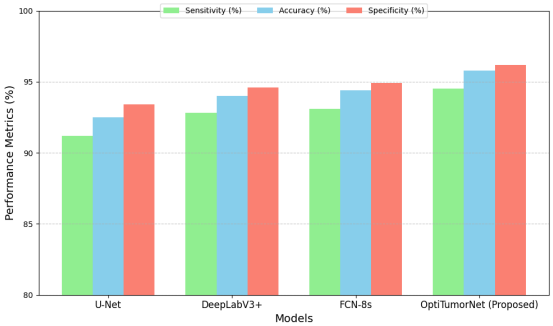


Fig. 2: Comparison of Model Performance Metrics

Figure 3 illustrates the comparison of two of the most critical performance metrics in the form of DSC and IoU, for four of the most utilized segmentation models. The result is such that OptiTumorNet records the highest value for both the metrics in terms of DSC being 0.910 and IoU being 0.850, indicating better segmentation accuracy as well as overlap with ground truth compared to other models. Even though U-Net, DeepLabV3+, and FCN-8s are good, their values of DSC and IoU being lower indicate scope for improvement in delineation of tumor regions. The improved performance of OptiTumorNet proves the effectiveness of the hybrid GWO-WOA optimization method in enhancing feature selection and hyperparameter tuning process to achieve improved segmentation quality. The outcomes validate the novelty and effectiveness of the proposed solution for addressing complex brain tumor segmentation issues.

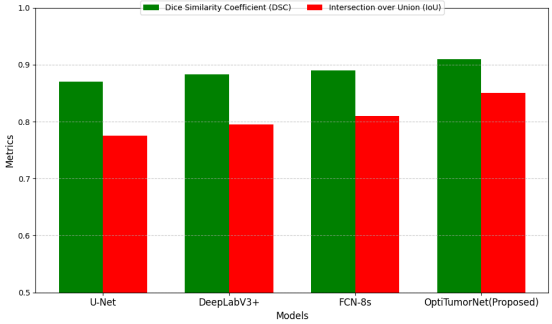


Fig. 3: Performance Comparison of Existing Models for DSC and IoU Metrics

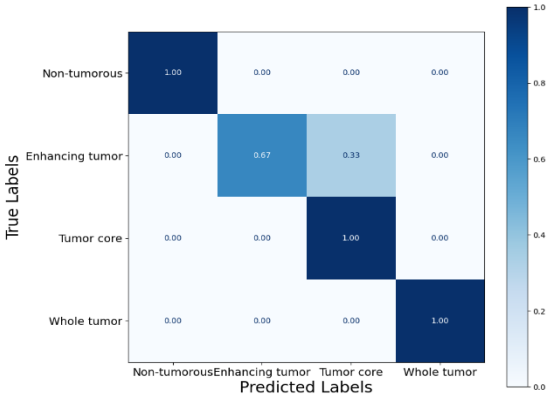


Fig. 4: Confusion Matrix for Segmentation

Figure 4 illustrates the segmentation confusion matrix, which compares the deep learning model's classification accuracy in four classes of brain tissue: Non-tumorous, Enhancing tumor, Tumor core, and Whole tumor. The diagonal elements indicate correct classification (true positives). For this example, the Non-tumorous, Tumor core, and Whole tumor classes achieved a perfect 1.00 score, indicating correct classification. Conversely, the Enhancing tumor class had a degree of misclassification with 67% correctly classified and 33% misclassified as Tumor core. This shows that the model struggles to differentiate between extremely similar tumor classes. The off-diagonal elements reflect such misclassifications, while the very high diagonal values confirm that the model well isolates tumor areas with high accuracy,

particularly the Non-tumorous, Tumor core, and Whole tumor classes.

Ablation Study

To validate the effectiveness of the hybrid GWO-WOA optimization, an ablation study was conducted comparing the use of GWO-only, WOA-only, and the hybrid GWO-WOA approach. Table 4 summarizes the results.

Table 4: Ablation Study of Optimization Techniques

Optimization Technique	DSC	IoU	ACC	Sensitivity	Specificity
GWO Optimization	0.885	0.780	93.1%	91.8%	93.9%
WOA Optimization	0.890	0.800	93.7%	92.3%	94.3%
Hybrid GWO-WOA (Proposed)	0.910	0.850	95.8%	94.5%	96.2%

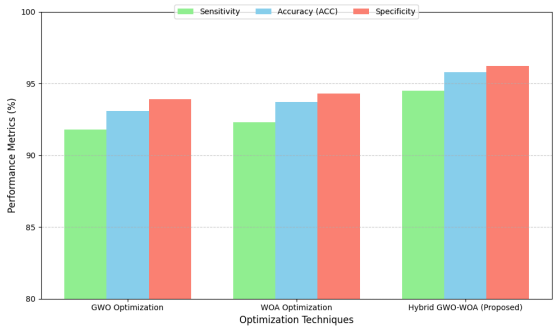


Fig. 5: Comparison of Optimization Techniques Performance Metrics

From the Figure 5, it can be observed that the proposed hybrid optimization process highly outperforms the individual processes. The Hybrid GWO-WOA has an accuracy of 95.8% which outperforms the GWO (93.1%) and WOA (93.7%) approaches. Similarly, in sensitivity, the hybrid method gets 94.5%, whereas GWO and WOA get 91.8% and 92.3%, respectively. In specificity, Hybrid GWO-WOA gets 96.2%, which is higher than individual GWO (93.9%) and WOA (94.3%) optimizations. These results point to the enhanced capability of the hybrid method to optimize the parameters of deep learning model, leading to improved brain tumor segmentation. The enhancement of all the metrics indicates towards the robustness of the developed approach to become more precise and reliable than individual optimization methods.

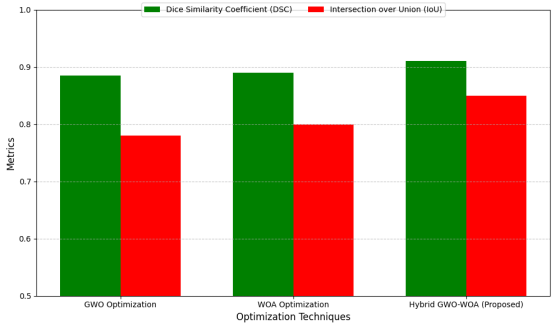


Fig. 6: Comparison of Optimization Techniques for DSC and IoU Metrics

Figure 6 clearly demonstrate the superiority of the hybrid optimization approach over standalone techniques. The Hybrid GWO-WOA, proposed in this work, achieved a DSC of 0.910, which is much higher than that of 0.885 achieved by GWO and 0.890 achieved by WOA. Similarly, in IoU, Hybrid GWO-WOA achieved 0.850, better than GWO (0.780) and WOA (0.800). The enhancement validates the synergistic integration of GWO-WOA algorithms, which optimizes the hyperparameters and threshold of the model appropriately for higher segmentation accuracy. The significant improvement in DSC and IoU values indicates the strength and accuracy of the hybrid method in accurate boundary delineation of tumors over single optimization methods. The results validate the novelty and competence of the proposed method in enhancing segmentation. The findings indicate that the hybrid optimization method outperforms single algorithms, indicating the advantage of merging GWO's global search ability with WOA's local exploitation ability.

Qualitative Results

Along with quantitative assessment, qualitative analysis was also performed. OptiTumorNet segmentation results were visually compared with those of other methods on carefully selected test images. These visualizations helped to demonstrate that OptiTumorNet generates sharper and more precise boundaries, particularly in challenging regions with intricate shapes, where conventional methods fail.

Preprocessed Images prior to OptiTumorNet Segmentation

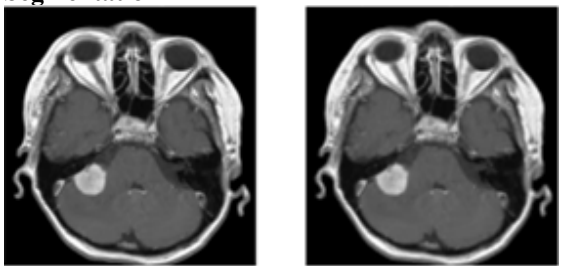


Fig. 7: Original and preprocessed images of OptiTumorNet

Figure 7 illustrates the preprocessing step, which is a critical process for improving the performance of brain tumor segmentation in deep learning models.

The preprocessed MRI scan is illustrated on the left-hand side, and enhanced input data are utilized for precise analysis. The preprocessing step consists of steps that are required to improve image quality and ensure consistency, thus making clarity and homogeneity in MRI scans improved. This includes noise reduction by using advanced filtering techniques to remove unwanted artifacts, normalization to standardize intensity values across scans, and resizing or cropping of the images to a particular size suitable for the deep learning algorithm. Skull stripping and ROI segmentation are also used to isolate the brain region from non-essential structures. This preprocessing method helps optimize the performace of the deep learning model, such as OptiTumorNet, is focused on tumor-relevant features and discards extraneous data. By doing this, the model becomes more efficient and reliable when detecting and segmenting tumor regions, laying a solid ground for the subsequent segmentation process.

Enhanced Brain Tumor Segmentation with OptiTumorNet

Figure 8 shows a graphical illustration of the segmentation process. The left image is the preprocessed MRI scan, prepared for analysis by normalizing intensity values and removing noise, and the right image shows the segmentation output, where the tumor region is well identified. This segmentation output proves the efficiency of the proposed OptiTumorNet framework in isolating tumor regions with high accuracy compared to other methods. By applying a mixed optimization approach GWO-WOA, OptiTumorNet effectively tunes the parameters of the deep learning model, making it more accurate and robust. The segmentation output confirms the framework's effectiveness in precisely delineating the border of tumors from normal brain tissue, more so compared to traditional approaches when it comes to speed and stability. Improved segmentation accuracy plays a vital role in facilitating precise diagnosis and treatment planning, highlighting the superiority of the proposed model compared to traditional methods.

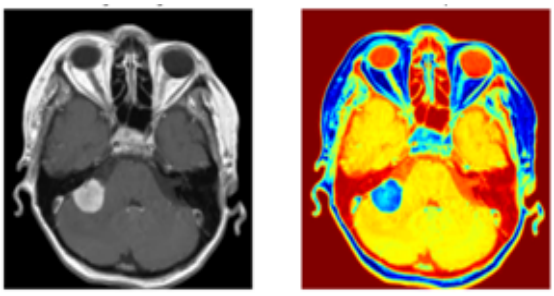


Fig. 8: Segmentation with OptiTumorNet

The innovation of the suggested framework is the hybrid optimization approach, where GWO and WOA are combined smoothly. The method can efficiently solve the exploration-exploitation trade-off in parameter optimization, leading to improved generalization and segmentation accuracy. Hyperparameter optimization and feature selection improve the performance without adding much computational burden. By surpassing state-of-the-art models, OptiTumorNet is an efficient and strong brain tumor segmentation framework that opens doors to potential future applications in medical imaging and diagnostics. The notable improvements in segmentation accuracy and computational efficiency reveal the potential of hybrid nature-inspired optimization techniques in deep learning-based healthcare solutions. The outcomes confirm the success of OptiTumorNet for segmenting brain tumors. The hybrid optimization methods provide higher accuracy in segmentation at low computational costs. The model shows improved performance in overlap measurements like DSC and IoU, which can prove to be an effective tool in computer-assisted tumor diagnosis. In addition, the findings of this work can motivate the improvements in medical image analysis and can help to establish more accurate diagnostic tools for practical use in clinical applications.

Conclusion and Future Work

This research introduced OptiTumorNet, a nature-inspired hybrid optimization architecture that synergistically integrates the Grey Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA) to improve the efficiency of deep learning-based brain tumor segmentation. With an enhanced U-Net backbone as the foundation, the proposed model utilizes the exploratory capability of GWO and the exploitative accuracy of WOA to optimize key parameters like feature selection, thresholding, and hyperparameter optimization. Experimental validation with the BraTS2021 dataset proved that OptiTumorNet systematically surpassed state-of-the-art architectures like U-Net, DeepLabV3+, and FCN-8s, with an outstanding accuracy of 95.8%, sensitivity of 94.5%, and specificity of 96.2%, with Dice Similarity Coefficient (DSC) of 0.910 and Intersection over Union (IoU) of 0.850. These results affirm the model's better ability to provide accurate, stable, and reliable tumor segmentation, particularly in complicated or irregular tumor areas. OptiTumorNet's innovation is in its capacity to unify two orthogonal optimization paradigms - the global exploration capability of GWO and the local exploitation power of WOA under a deep learning framework, thus preventing overfitting and promoting generalization. Hybridizing these paradigms not only enhances segmentation performance but also has more stable convergence properties than single-optimizer-based systems.

Though having good results, the proposed work has some limitations. The hybrid optimization system has very high training-time computational overhead, which can restrict its use in low-resource or real-time clinical environments. The noisy or

missing MRI data sensitivity in the model can at times decrease segmentation accuracy, especially in low-contrast image settings.

As a continuation of this work, computational costs can be lessened with lightweight optimization methods, parallel computation, or cloud-based distributed training. Furthermore, extending OptiTumorNet to process multi-modal imaging (e.g., combining MRI, CT, and PET data) may further enhance segmentation accuracy and cross-modal generalizability. Adding explainable AI (XAI) elements to the framework would increase interpretability, thus making the system more transparent and clinically reliable for doctors. Another potential direction is the creation of a real-time deployment module or web-based clinical interface for practical implementation into hospital workflows. In short, OptiTumorNet forms a strong foundation for optimal deep learning-based brain tumor segmentation. By harmonizing advanced optimization approaches with medical imaging, this work opens an open window for further investigation, pointing toward more intelligent, efficient, and clinically interpretable segmentation systems in the future.

Abbreviation

CNN: Convolutional Neural Networks
GWO: Grey Wolf Optimization
WOA: Whale Optimization Algorithm
MRI: Magnetic Resonance Imaging
PSO: Particle Swarm Optimization
DSC: Dice Similarity Coefficient
IoU: Intersection over Union

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