# Transformer Network-based Image Segmentation using Hybrid Flower Pollination Optimization

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***Abstract*— Effective image segmentation is important in various fields, from medical imaging to autonomous vehicles. This paper presents an integration of Hybrid Flower Pollination Optimization (HFPO) with Transformer networks, considering strengths of global optimization and deep learning. HFPO, inspired by natural pollination processes, excels in exploring vast solution spaces, while Transformers, renowned in deep learning, capture complex patterns. This fusion enhances segmentation accuracy and computational efficiency. Balancing sophistication and computational feasibility, this approach marks a significant advancement in image analysis, promising transformative applications across industries. The experimentation and evaluation, reveal that the proposed HFPO- Transformer based model for image segmentation is more efficient than the existing methods.**

***Keywords*— *Image Segmentation, Hybrid Flower Pollination Optimization, Transformer Networks, Computer Vision, Deep Learning.***

## I. Introduction

In the fields of computer vision and artificial intelligence, precise segmentation of complex images remains a fundamental challenge for diverse applications, from medical diagnostics to autonomous systems. Traditional methods often struggle with identifying complex spatial relationships within images and provide better solutions. This paper introduces the framework, referred to as "HFPO-Transformer" (Hybrid Flower Pollination optimization), which integrates HFPO-driven parameter selection with trans- former architecture. HFPO, a nature-inspired optimization algorithm, excels in the global exploration of solution spaces, while Transformers, originally designed for natural language processing, exhibit exceptional prowess in capturing intricate patterns within data. By fusing the abilities of HFPO with the deep learning capabilities of Transformers, the proposed work aims to provide better accuracy for image segmentation. Through this integration, our proposed approach represents a significant improvement towards the future of computer vision, by analyzing and interpreting complex visual information.

## II. Literature Survey

Recent advancements in computer vision and optimization techniques have made image segmentation, a critical component of numerous applications including disease diagnosis, autonomous vehicles, and robotics. Early research efforts such as [1-5] explored the application of genetic algorithms (GA) for image segmentation, demonstrating the potential of evolutionary techniques in optimizing segmentation parameters. Subsequently, authors of papers [6-10], introduced Particle Swarm Optimization (PSO) as an effective tool for optimizing segmentation algorithms, for improved convergence rates and segmentation quality. The rise of deep learning models, particularly Convolutional Neural Networks (CNNs), reshaped image analysis. Authors of [15-17] utilized CNNs' ability to automatically learn features from data, significantly enhancing segmentation accuracy. Also, challenges persisted in fine-tuning complex networks, prompting exploration into hybrid methods. Recent literature, such as [18-21], proposed the integration of optimization algorithms with Transformer architectures, originally designed for sequence modeling tasks. Transformer models, known for their attention mechanisms, were adapted to capture complicated spatial dependencies within images, as demonstrated by [22-25]. Fusion of these architectures with evolutionary algorithms, like Flower Pollination Optimization (FPO) and its hybrid variants, as discussed in [11- 14], led to significant advancements in both accuracy and computational efficiency. However, the research gap remains in exploring the integration of Hybrid Flower Pollination Optimization (HFPO) with Transformer networks for image segmentation tasks. Our proposed work seeks to address this gap by proposing hybrid HFPO and transformer based approach for image segmentation.

## III. METHODOLOGY

This section, briefs about the steps of HFPO-Transformer Model to perform image segmentation task. The steps of HFPO-Transformer model for performing image segmentation have been specified in Fig. 1. Initial step is to gather dataset samples to perform image segmentation. The proposed work utilizes BRATS (Brain Tumor Segmentation) dataset from Kaggle. The proposed approach, Hybrid Flower Pollination Optimization with Transformer (HFPO-Transformer), is a hybrid optimization technique applied for image segmentation. This approach fuses hybrid flower pollination algorithm with transformer architecture for better accuracy and efficiency in performing image segmentation.

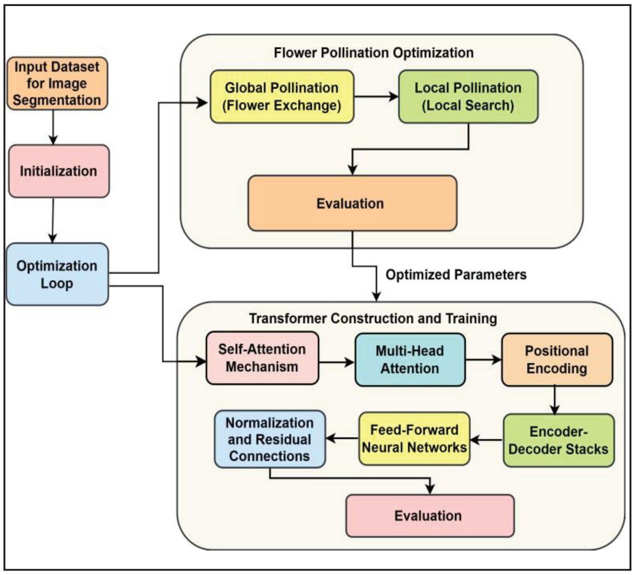


Fig. 1. Image Segmentation Utilizing HFPO-Transformer Approach

Fig. 1 represents the proposed framework involving iterative process of flower pollination-guided optimal parameter selection and demonstrates how transformer architecture is used with each step, from fitness evaluation to final model training and performance evaluation. The first step involves setting up the initial values for the FPO optimization process. This process involves initializing the parameters of FPO and selected transformer network. Parameters for FPO, such as population size, pollination coefficients (α,β), and maximum iterations, are initialized. Hyperparameters for Transformer network, like the number of layers, attention heads, and learning rate, are also initialized. Suitable transformers for image segmentation will be vision transformers and also the selection depends on the requirements of applications.

The next step is performing global and local pollination processes. During this process, FPO iteratively explores the solution space. Flowers represent sets of Transformer hyperparameters exchange information globally and locally, imitating the pollination behavior of flowers. Global pollination computation specified in equation 1 explores diverse solutions, while local pollination specified in equation 2 refines solutions in specific areas of search space. The fitness of each set of hyperparameters is evaluated using a fitness function specified in equation 3. Fitness can be based on metrics like the Dice coefficient, representing the accuracy of segmentation. Flowers with higher fitness values are selected for the next iteration. Hybridization can be used in the process of flower pollination depending on the complexity of problem, dimension of solution space, and computational resources. Considering these aspect FPO can be combined with optimization methods such as genetic algorithms, differential evolution, particle swarm optimization. This method ensures a comprehensive search across solution space while fine-tuning solutions in promising regions, leading to better optimization results. By integrating diverse algorithms, HFPO can utilize the strengths of each method to converge faster toward optimal solutions.

Next, the optimized set of hyperparameters obtained from FPO is used to construct a Transformer network. The network architecture is set up according to selected hyperparameters. The constructed Transformer network is trained using image dataset. The network learns to map input images to segmented output using a supervised training approach. Training involves minimizing a loss function, often related to the dissimilarity between predicted and ground truth segmentations. trained Transformer models are evaluated using validation data. The model with best performance, usually measured by accuracy, Dice coefficient, and other metrics, is selected as the optimized model configuration. The final output of the proposed method is accurately segmented images, obtained by optimizing the Transformer network's hyperparameters through the FPO process. The steps of the proposed HFPO-Transformer algorithm is specified below.

**Algorithm: HFPO-Transformer for Image Segmentation**

Step 1: Initialization:
- Initialize FPO parameters: population size, maximum iterations, mutation rate, etc.
- Initialize Transformer parameters: layers, attention heads, learning rate, etc.
- Define the fitness function based on the segmentation accuracy.

Step 2: Data Preparation:
- Load and preprocess the image dataset, ensuring compatibility with the input format expected by the Transformer network.

Step 3: Generate Initial Population:
- Generate an initial population of solutions using FPO.
- Each solution represents a set of hyperparameters for the Trans- former network.

Step 4: FPO Optimization Loop:
- Global Pollination:
  $$xi(t+1) = xi(t) + \beta \times (xj(t) - xk(t)) \quad (1)$$
- Local Pollination:
  $$xi(t+1) = \mathrm{x}(t) + \alpha \times (xi(t) - xj(t)) \quad (2)$$

Here, xi (t+1) represents the updated position of the $i^{th}$ flower (solution) at iteration t+1. $x_j$ (t) and $x_k$ (t) represent positions of other flowers selected for pollination. α and β are pollination coefficients controlling the exploration intensity.

- Evaluate the fitness of each solution after pollination using equation 3.
  Fitness($xi$) = $DSC$ ($Predicted\ Segmentation$, $Ground\ Truth$) (3)

Fitness function can be formulated based on the segmentation accuracy and other evaluation metrics. For example, using Dice coefficient specified as DSC in equation

Step 5: Apply Transformers:

- For each solution in the final population, construct a Transformer network with the corresponding hyperparameters.
- Train the Transformer network using the medical image dataset.
- Evaluate the segmentation accuracy and other metrics for each trained Transformer.

Step 6: Select Best Solution:

- Choose the solution (set of hyperparameters) that resulted in the highest segmentation accuracy.
- This solution represents the optimized configuration for the Transformer network.

Model performance is then assessed based on the optimal parameters selected for the segmentation task. The final step is to perform model evaluation using performance metrics as specified in Table I. Thus, HFPO-Transformer approach enhances the process of segmentation by generating optimal parameters using HFPO based on the data samples.

## IV. RESULTS

The dataset used in the HFPO-Transformer approach is the BRATS (Brain Tumor Segmentation) dataset from Kaggle. This dataset is a classic benchmark used for image segmentation tasks. It offers high-resolution MRI scans of the brain with detailed pixel-wise annotations delineating various brain tumor types, including gliomas and meningiomas. These annotations provide the ground truth for tumor segmentation algorithms, indicating the exact location and extent of tumors. Different tumor types exhibit distinct characteristics in imaging, making the dataset diverse and challenging. This dataset serves as a benchmark for developing and evaluating advanced algorithms in brain tumor segmentation. MRI images in the BRATS dataset are typically high-resolution, allowing for detailed examination of brain structures and abnormalities.

The sample MRI brain tumor image and ground truth prediction is specified in Fig. 2. Ground truth data are crucial in image segmentation tasks as they provide the standard against which algorithmic outputs are measured, considering accuracy of segmentation results. Convergence of HFPO signifies the algorithm's ability to iteratively explore and refine parameters to improve segmentation task. The convergence of the HFPO-Transformer model based on number of epochs in terms of loss function during training is specified in Fig. 3.

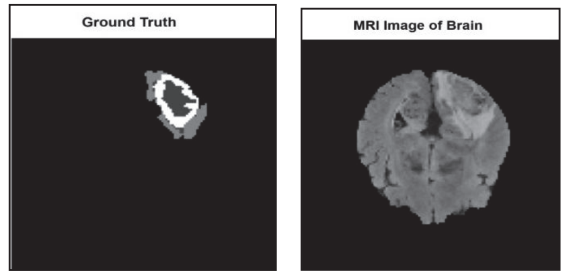


Fig. 2. Sample MRI Image and Ground Truth Prediction

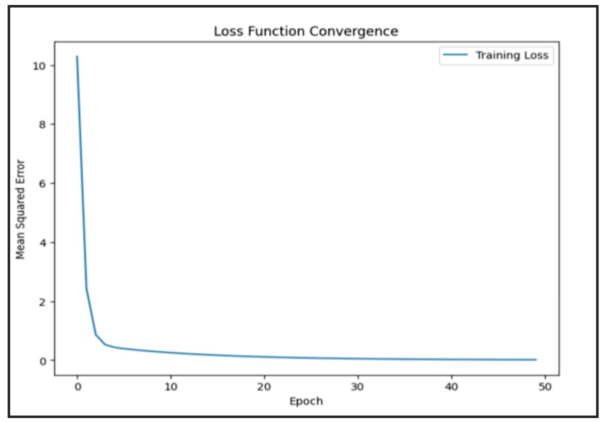


Fig. 3. HFPO-Transformer model convergence during training based on epochs

The proposed work integrates HFPO with the transformer network for optimal parameter selection to perform segmentation. HFPO outputs optimized parameters, required for accurate segmentation. The transformer model is trained with the selected parameters derived from HFPO stage and then evaluation is performed using relevant metrics. The final output of combined approach is an effective and optimized segmentation model that utilizes the power of HFPO for optimal parameter selection.

This method enhances segmentation accuracy and helps in applications like medical diagnosis, plant disease identification, and more. Performance evaluation of HFPO-Transformer model with relevant metrics is specified in Table I.

The details reveal that the HFPO-Transformer model performs well compared to existing approaches in performing segmentation tasks. Table II outlines the hyperparameter tuning process for HFPO stage in the proposed approach. This process is iterative and involves systematically experimenting with various hyperparameter settings to identify optimal configuration that maximizes performance for a specific segmentation task and dataset. Also, hyperparameters for the transformer vary depending on the architecture selected for segmentation.

TABLE I. EVALUATION OF HFPO-TRANSFORMER APPROACH FOR IMAGE SEGMENTATION

| Method | Dice Coeffi-cient | Sensitivity | Specificity | Accuracy | F1-Score |
|---|---|---|---|---|---|
| CNN | 0.78 | 0.81 | 0.90 | 0.85 | 0.79 |
| U-Net with ResNet | 0.82 | 0.86 | 0.88 | 0.87 | 0.82 |
| Deep Attention Network | 0.79 | 0.83 | 0.91 | 0.86 | 0.80 |
| ProposedHFPO-transformer model | 0.85 | 0.88 | 0.92 | 0.89 | 0.86 |

TABLE II. HYPERPARAMETER TUNING VALUES FOR HPFO-TRANSFORMER MODEL

| Hyperparameter | Description | Candidate Values/Range | Best Value |
|---|---|---|---|
| Population Size (N) | Number of individ uals in the population | [20, 100] | 50 |
| Maximum Iterations | Number of iterations for HFPO | [500, 2000] | 1000 |
| Local Pollination Co-efficient | Weight for local pollination exploration | [0.1, 1.0] | 0.5 |
| Global Pollination Co-efficient | Weight for global pollination exploration | [0.1, 1.0] | 0.2 |
| Learning Rate | Step size for updating model parameters | [0.0001, 0.1] | [0.001] |
| Number of Trans-former Layers | Depth of the Trans-former model | [3, 12] | [6] |
| Number of Attention Heads | Number of attention heads in the Transformer model | [4, 16] | [8] |
| Hidden-Units in Feed-forward Layers | Number of hidden units in the Trans-former feed-forward layers | [256, 1024] | [512] |
| Batch Size | Number of samples used in each iteration of training | [16, 64] | 32 |
| Loss Function | Objective function used for model optimization | [Dice Loss, Cross-Entropy, etc.] | [DiceLoss] |

## CONCLUSION

The fusion of Hybrid Flower Pollination Optimization (HFPO) and Transformer networks has yielded a feasible solution for image segmentation, particularly in brain tumor analysis. Through experimentation and evaluation, HFPO-Transformer method has demonstrated better accuracy and efficiency, and can be used effectively in analysing medical images. Ability of proposed approach to handle diverse tumor types and optimize computational resources, not only advances the accuracy of segmentation but also has the potential to be used in clinical applications. Experimental evaluation shown that HFPO-Transformer framework offers significant advantages over conventional methods and standalone deep learning based approach. The integration of Hybrid Flower Pollination Optimization with Transformer networks not only promises advancements in medical image segmentation but also extends its applications to diverse healthcare domains. Future research should explore the potential of hybrid approach in fields like personalized medicine, real-time data analysis, and healthcare optimization, paving the way for more efficient, accessible healthcare solutions globally. Further, the research can focus on enhancing and developing parallel computing strategies for more image segmentation in large-scale datasets.

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