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AN ADAPTIVE FRACTIONAL DEEP LEARNING MODEL FOR ACCURATE MEDICAL IMAGE SEGMENTATION

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ABSTRACT

Medical image segmentation plays a crucial role in computer-aided diagnosis, disease monitoring, and clinical decisions. Existing deep learning segmentation methods perform poorly in low-contrast regions, at edges, and across different anatomical regions of the human body. This investigation presents an Adaptive Fractional Deep Learning Model (AFDLM) for high-accuracy medical image segmentation. The model integrates Adaptive Fractional Convolution (AFC) Operations, the Fractional Adaptive Attention Module (FAAM), and the Fractional Gradient Optimization Strategy (FGOS). The proposed framework provides a more informative context for feature extraction. It also maintains high accuracy in delineating fine anatomical details and helps preserve segmentation accuracy, even in the presence of imaging noise. A series of experiments has been carried out on normalized metrics, including Dice Similarity Coefficient (DSC) for brain tumor MRI, Lung CT, and Retinal Vessel data sets, as well as Intersection over Union (IoU), Precision, Recall, and Hausdorff Distance (HD). The proposed AFDLM has achieved high performance, outperforming previous models such as U-Net, Attention U-Net, DeepLabV3+, and TransUNet, with an average DSC of 94.0% and an IoU of 89.3%. The visual analysis also showed that the vessels were preserved, lesion edges were well delineated, and extraction of low-contrast lesions was improved. Adaptive fractional operations enable robust segmentation across multiple modalities is achieved using adaptive fractional operations, which yield inter-segmentation noise reduction and improved structural consistency. The proposed framework suggests that fractional deep learning is an intriguing future path for a next-generation medical image segmentation system with enhanced capabilities to support diagnosis and high clinical reliability.

Keywords: *Medical Image Segmentation; Fractional Deep Learning; Adaptive Attention Mechanism; Brain Tumor Segmentation; Lung CT Analysis; Retinal Vessel Extraction*

1. INTRODUCTION

Segmentation of medical images has been a major focus in biomedical image analysis research fields due to its importance in medical diagnosis, therapy planning, organ delineation, and surgical assistance. The segmentation process can be used to detect lesions, blood vessels, and tumors in images.

These images are acquired from modalities such as histology, retinal fundus images, MRI, CT, and ultrasound [1]. Recently, as healthcare systems have become more intelligent, automated segmentation has grown important for helping physicians diagnose and improve clinical efficiency.

Historically, segmentation techniques in medical imaging included thresholding, clustering, region growing, and active contour models [2]. Problems such as noise, low contrast, indistinct geographical borders, and patient-to-patient variability create challenges for these methods. Moreover, handcrafted feature extraction methods are neither robust nor generalizable across heterogeneous image sets [3].

In recent years, medical image segmentation has been transformed by deep learning. Convolutional Neural Networks (CNNs) can automatically learn hierarchical feature representations and greatly improve segmentation [4]. Encoder-decoder learning and skip connections have been key to the outstanding success of architectures like Fully Convolutional Networks (FCNs) and U-Net [5]. The advanced variants, such as Attention U-Net and U-Net++, further improved the contextual learning and feature propagation [6], [7]. Although these developments have come a long way, current deep learning models still lack the ability to retain fine spatial detail, especially after multiple pooling layers, and to understand long-range contextual information [8]. In addition, segmentation performance is often impaired in noisy, low-contrast imaging scenarios [9].

Recently, transformer models have shown that global contextual learning can be enhanced by modeling self-attention, as in Vision Transformers, TransUNet, and Swin-UNet [10]. Generally, these models require substantial computing power and large annotated datasets, limiting their use in practice [11]. Hence, an efficient segmentation framework that can preserve fine anatomical boundaries while maintaining strong contextual understanding is still required.

Recently, fractional-order calculus has attracted interest in image processing due to its modeling of non-local dependence and the continuity of texture [12]. Fractional differential operators have demonstrated promising results in image enhancement, denoising, and edge preservation applications. The fusion of fractional calculus and deep learning-based medical image segmentation, however, remains rather unexplored, which inspires researchers to develop the proposed Adaptive Fractional Deep Learning Model (AFDLM).

Acknowledging the above shortcomings and inspired by such thoughts, this work introduces an Adaptive Fractional Deep Learning Model (AFDLM) for precise segmentation of medical images. The proposed adaptive fractional convolutional operations and the Fractional Adaptive Attention Module (FAAM) are designed to improve feature representation and boundary preservation. Additionally, a Fractional Gradient Optimization Strategy (FGOS) was developed. It helps facilitate faster convergence during training and better generalization across different imaging modalities.

The proposed research has six principal goals as listed below:

i) To develop an adaptive fractional deep learning approach to medical image segmentation for deep learning.

ii) To implement fractional convolution operators for better texture and boundary modeling.

iii) To effectively learn contextual features by designing a Fractional Adaptive Attention Module.

iv) To obtain more accurate segmentation in noisy and low-contrast images.

v) To assess how well the proposed framework performs using multiple benchmark medical imaging datasets.

vi) To compare the state-of-the-art segmentation architecture based on the proposed model to common evaluation metrics.

The main contributions are: (i) the Adaptive Fractional Deep Learning Model (AFDLM), which combines fractional calculus with deep segmentation networks, (ii) Adaptive Fractional Convolution (AFC) operations to preserve boundaries and convey texture, (iii) the Fractional Attention Module (FAAM) to learn contextual features and localize anatomical structures, (iv) the Fractional Gradient Optimization Strategy (FGOS) to enhance convergence stability and model generalization, and (v) extensive validation of AFDLM on three public datasets—Brain Tumor MRI, Lung CT, and Retinal Vessel—demonstrating strong performance compared to conventional CNN- and transformer-based segmentation models.

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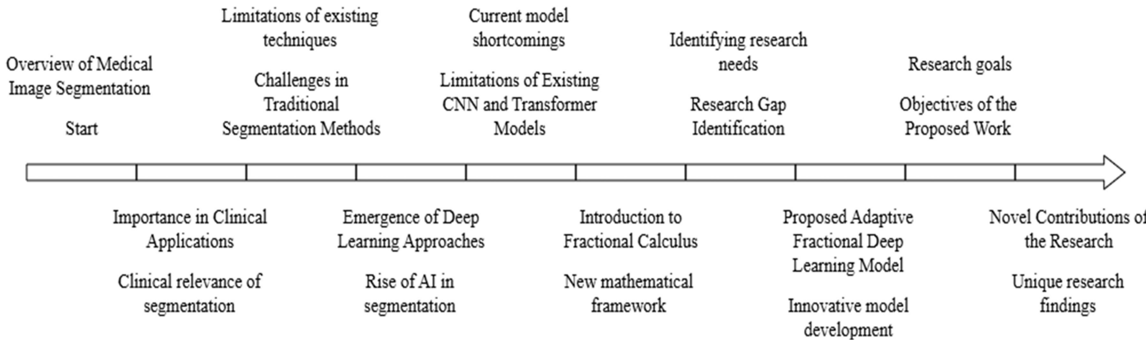

Figure 1. *Research Motivation and Development Process of the Proposed AFDLM Framework for Adaptive Fractional Deep Learning-Based Medical Image Segmentation*

As shown in Figure 1, the conceptual flow of the proposed research for the new Adaptive fractional deep learning for medical image segmentation is presented. The flowchart starts with an introduction to the medical image segmentation and its clinical relevance. Correct segmentation of medical images is crucial for medical image processing. It then discusses the shortcomings of conventional segmentation methods and the use of deep learning models, such as CNNs and transformer-based models.

The figure also shows the areas where current deep learning techniques fall short, including inadequate boundary representation and high computational costs, and proposes a novel mathematical approach, fractional calculus, for improved feature representation in deep learning. The research gap is identified, which inspires us to develop our proposed Adaptive Fractional Deep Learning Model (AFDLM). Lastly, the research aims summarized in a flowchart were included along with novelties and expected outcomes of the proposed research.

The novelty of the proposed work lies in the adaptive use of fractional calculus in deep segmentation networks to better preserve fine anatomical structures and enhance contextual discrimination. The proposed AFDLM differs from existing CNN and transformer methods by dynamically tracking fractional parameters during training to adapt to the heterogeneous characteristics of medical images. In addition, the segmentation errors near object boundaries are reduced, and convergence stability is enhanced by the proposed fractional optimization procedure.

The rest of this paper was structured as follows. We provided an in-depth review of previously used medical image segmentation techniques in Section II, including classical methods, deep learning models, transformer-based models, and fractional calculus methods. In Section III, the proposed Adaptive Fractional Deep Learning Model (AFDLM) is incorporated. Description, dataset details, preprocessing techniques, architectural designing, mathematical modeling, optimization methodology, and algorithmic implementation are described here. The experimental results were presented in section IV, along with the performance evaluation criteria, comparisons with related models, graphical interpretations, and ablation studies. At last, Section V provided a summary of the main results, constraints, and the outlook for further investigation in the suggested framework.

2. RELATED WORK

In medical image segmentation, significant progress has been made in recent years, driven by advances in artificial intelligence, deep learning, and computational techniques. There are several segmentation methods, which can be roughly divided into conventional machine learning methods, convolutional neural network (CNN) architectures, transformer-based models, attention mechanisms, and fractional calculus models.

Initial models based on machine learning applied hand-crafted feature approaches and statistical modeling algorithms, including support vector machines (SVMs) and random forests (RFs) [13]. Moderate segmentation accuracy led to techniques that were neither robust nor adaptable to other types of medical images. Thanks to advances in deep convolutional neural networks, semantic feature representation, and end-to-end medical image segmentation, significant progress has been made [14]. The encoder-decoder architecture was the first to become popular, as it provides a means to store information from the context level at the pixel classification stage. To ensure good connectivity and prevent information loss within the model, two mechanisms involving residual and dense connections were added [15], [16]. This use facilitated good gradient flow and yielded consistent segmentation, though it was limited by noise or low-contrast imaging. Later, 3D segmentation frameworks were developed for volumetric analysis of MRI and CT images, enabling higher spatial continuity in learning between neighboring slice images [17]. Although effective, these approaches demanded computational and memory resources and weren't economically feasible.

For segmentation, attention mechanisms were later introduced in the networks to enhance feature selection and region localization [18]. The identification of regions of interest, which contained diagnostically relevant information, was strengthened and distracting background information was suppressed, thanks to a "channel attention module" and a "spatial attention module. Later, transformer-based models have been shown to better model long-range dependencies and global context through self-attention [19], [20]. Next, CNN-based transformers improved segmentation results by effectively integrating local feature extraction with global reasoning [21]. These architectures, however, are typically more complex in terms of the number of parameters studied and the computational cost of those parameters.

Segmentation of medical images remains difficult when images are low-contrast and noisy. To further enhance segmentation robustness and generalization performance, Generative Adversarial Learning and Semi-supervised learning approaches were proposed [22], [23]. However, there are potential problems, such as training instability and performance degradation in a heterogeneous imaging environment.

In the past, some image processing algorithms have been based on fractional calculus, selecting edge information while maintaining the continuity of the texture [24]. Fractional differential operators exhibited better performance—which is especially notable in the sense of capturing the fine structural variations—in the solution of fine variations. Recently, fractional-order optimization and fractional deep learning mechanisms for Biomedical image analysis have also been explored [25]. The coupling of adaptive fractional operations to deep segmentation architectures is yet to be exploited to the extent.

Previously published papers also mentioned issues such as a lack of boundary maintenance, boundary disconnection, and reduced generalization potential across different imaging modalities. To address these restrictions, a newly proposed scheme, the Adaptive Fractional Deep Learning Model (AFDLM), was introduced, combining adaptive fractional convolution, attention learning, and fractional optimization to improve segmentation accuracy and the continuity of structures.

Several key research gaps remain unaddressed:

i) Limited integration of fractional calculus with deep segmentation architectures.
ii) Insufficient adaptive learning of fractional parameters.
iii) Fine anatomic boundaries are poorly preserved.
iv) Transformer-based models require substantial computational resources.
v) Decreased robustness in (low contrast and) noisy imaging situations.
vi) Absence of generalization across medical imaging modalities.

These drawbacks have been overcome by the proposed Adaptive Fractional Deep Learning Model (AFDLM), which combines fractional convolution, an adaptive attention mechanism, and fractional gradient optimization into a single segmentation framework. The aim of the proposed approach is to enhance contextual understanding and maintain the structural continuity of heterogeneous medical imaging datasets while simultaneously boosting their segmentation accuracy.

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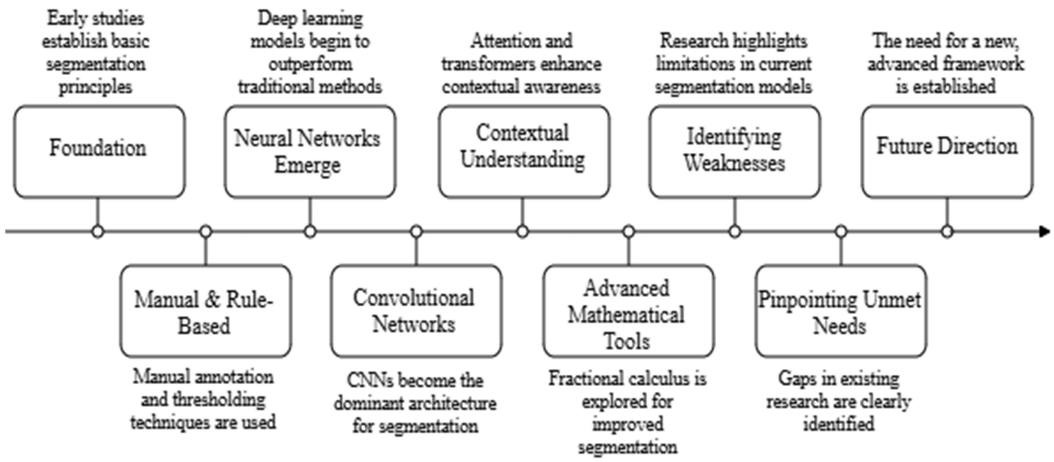

Figure 2. *Evolution of Medical Image Segmentation*

Figure 2 shows that medical image segmentation research has evolved from rule-based to intelligent methods. The flow begins by using basic segmentation techniques based on manual annotations and thresholding, relevant to medical image analysis.

The graph then demonstrates that, as time progressed, there was a gradual shift towards deep learning, and among deep learning systems, convolutional networks outperformed others due to their ability to learn to extract features from images. Later, transformer-based models have been developed to better capture context and pool over the entire content into representations used for segmentation.

In addition, this figure demonstrates the use of sophisticated mathematical techniques, such as fractional calculus, to improve texture preservation and boundary enhancement. However, several challenges still remain, including computational complexity, inadequate boundary preservation, and limited robustness to noisy medical images. Finally, the proposed Adaptive Fractional Deep Learning Model (AFDLM) is a new adaptive model for accurate and robust medical image segmentation, motivated by the flowchart.

Recently, CNN-, attention-, and transformer-based methods advanced medical image segmentation, but some issues remain: CNN models lose thin anatomical boundaries and long-range context, while transformer models require extensive data and computation. These methods have not proven sufficiently effective in the presence of noise and low contrast in clinical images. Thus, a framework is needed to represent local texture, boundary information, contextual dependencies, and varying imaging conditions. Integrating AFC, FA, and FGO in the proposed AFDLM addresses these shortcomings.

3. METHODOLOGY

3.1 Overview of the Proposed Framework

To overcome the aforementioned limitations, we present an Adaptive Fractional Deep Learning Model (AFDLM) that combines adaptive fractional calculus with deep convolutional networks and attention mechanisms to achieve highly accurate, robust medical image segmentation. It features novel algorithms for fractional convolution operations, adaptive feature refinement methods, and the Fractional Gradient Optimization Strategy (FGOS), which improves segmentation accuracy, particularly in medical imaging with noisy, low-contrast, and heterogeneous data. The suggested methodology begins with medical image acquisition and the preparation of benchmark MRI, CT, and Retinal image datasets for training, validation, and testing. Following this, any series of image preprocessing or normalization steps can be used to enhance image quality, denoise, and homogenize intensities across imaging modalities. After preprocessing, fine features with fine spatial texture and long-range context information are adaptively extracted using a fractional convolution layer, which improves this process compared with traditional convolution layers. The proposed method, Fractional Adaptive Attention Module (FAAM), contains three modules: namely, the spatial attention module, the channel attention module, and the fractional weighting module, which are used to highlight the parts of the image that are important to the diagnosis, while suppressing the information that is irrelevant to the diagnosis. A multi-scale contextual encoder-decoder segmentation framework is also used to

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learn both local structural details and global semantic representations, thereby further improving segmentation accuracy. The Fractional Gradient Optimization Strategy (FGOS) was used during the training phase to achieve stable convergence, optimize the parameters, and improve generalization. The decoder can then recover high-resolution segmentation masks without losing fine anatomical details and edge continuity by implementing adaptive skip-fusion strategies. Finally, using the common metrics for evaluating and validating the segmented outputs, such as the Dice Similarity Coefficient (DSC), Intersection over Union (IoU), precision, recall, and boundary accuracy. Overall, the novel architecture is designed to preserve fine anatomical structures, enhance contextual representation of structural features, ensure compatibility with segmentation information, and be suitable for real clinical applications, while offering satisfactory runtime performance.

3.2 Dataset Description

Experiments to assess the efficacy and generalisability of the AFDLM framework were conducted using three medical imaging datasets from public repositories.

3.2.1 Brain Tumor MRI Dataset

In this project, we make use of the publicly available Brain Tumor MRI dataset from figshare. A set of 3,064 contrast-enhanced MRI T1-weighted scans was obtained from 233 patients suffering from glioma, meningioma, and pituitary tumors. Supervised segmentation analysis is enabled by expert-annotated segmentation masks [26].

Table 1. *Brain Tumor MRI Dataset Characteristics*

Parameter	**Value**
Imaging Modality	MRI
Image Dimension	256 × 256
Number of Images	3,064
Tumor Classes	Glioma, Meningioma, Pituitary
Annotation Type	Pixel-wise segmentation masks
Color Format	Grayscale
Data Split	70% Training, 15% Validation, 15% Testing

The Brain Tumor MRI dataset specifications used to evaluate the proposed AFDLM model are summarized in Table 1. There are 3,064 grayscale MRI images, each with a pixel-wise segmentation mask for glioma, meningioma, and pituitary tumor. The images have been split into triplets for model development and performance (70:15:15) to form training, validation, and testing sets.

Sample MRI Images

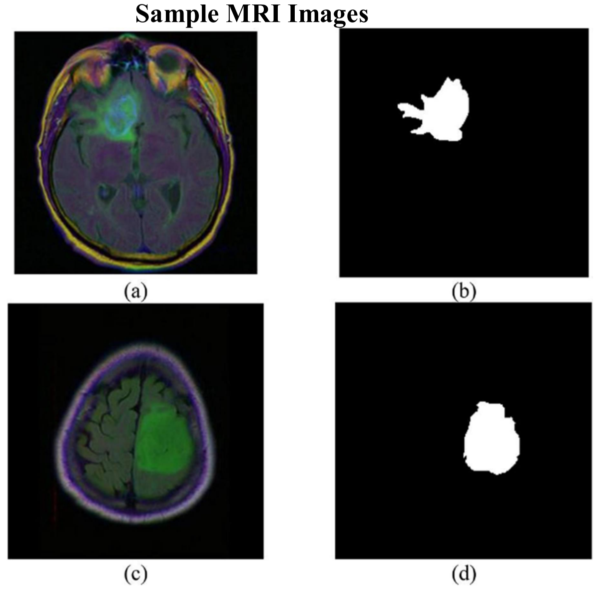

Figure 3. *Representative MRI brain tumor images and corresponding ground-truth segmentation masks from the benchmark dataset. Panels* (a) *and* (c) *illustrate input MRI scans, while panels* (b) *and* (d) *represent the associated binary tumor annotations used for supervised segmentation training and evaluation.*

3.2.2 Lung CT Segmentation Dataset

In this paper, we used the publicly available Lung CT Segmentation dataset of COVID-19 CT

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Lung and Infection Segmentation. Thoracic computed tomography (CT) with lung and infection masks, annotated by highly trained chest radiologists, has been included in the dataset. The dataset contains difficult, low-contrast lesion areas with various distributions of infection, which is suitable for testing the robustness of the proposed Adaptive Fractional Deep Learning Model (AFDLM) [27].

Table 2. *Lung CT Segmentation Dataset Characteristics*

Parameter	Value
Imaging Modality	CT
Slice Resolution	512 × 512
Number of CT Slices	2,670
Annotation Type	Binary lesion masks
Imaging Condition	Low-contrast pulmonary regions
Data Format	DICOM
Split Ratio	70:15:15

The characteristics of the Lung CT Segmentation dataset applied in our research are provided in Table 2. The data consists of 2670 512 × 512 pixel, binary lesion masks and corresponding center slices of CT data. These images are low-contrast pulmonary regions with comprehensive information stored in DICOM format, divided into training/validation/testing sets at 70:15:15.

Sample CT Image Characteristics

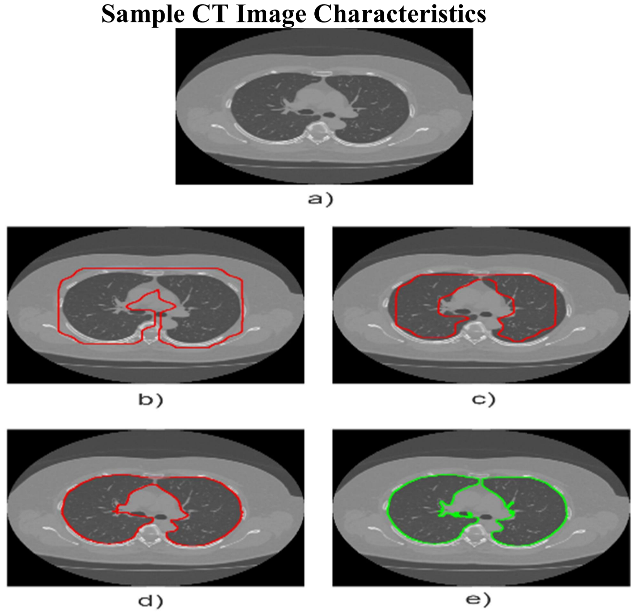

Figure 4. *Representative thoracic CT images with lung segmentation contour annotations. Panel* (a) *shows the original CT scan, while panels* (b)–(e) *illustrate different stages or outputs of lung region segmentation and contour refinement*

3.2.3 Retinal Vessel Segmentation Dataset

The retinal vessel segmentation experiments were performed on the publicly available DRIVE dataset. It consists of color retinal fundus images and manually labeled vessel masks from DR screening programs. The dataset contains complex vascular structures and fine vessel branches, which can be used to evaluate the boundary-preservation capability of the proposed Adaptive Fractional Deep Learning Model (AFDLM) [28]. The retinal dataset consists of fundus images and is used for vessel segmentation and ophthalmological analysis.

Table 3. *Retinal Vessel Segmentation Dataset Characteristics*

Parameter	Value
Imaging Modality	Retinal Fundus Imaging
Image Resolution	565 × 584
Number of Images	40
Annotation Type	Vessel masks
Dataset Type	Color retinal images
Data Split	70% Training, 15% Validation, 15% Testing

Table 3 shows the summary of the retinal fundus image dataset that was used for retinal vessel segmentation in this work. We have 40 retinal images with annotations of the vessels, more or less apparent, each in a given color, with a resolution of 565 × 584 pixels, supplied for supervised learning,

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along with the vessel mask annotation. The images are characterized by complex vascular patterns, fine vessel branching, and diverse illumination conditions, making segmentation highly challenging. The dataset is split into training, validation, and test sets at 70:15:15 for experimental evaluation and reproducibility.

Sample Retinal Image Characteristics

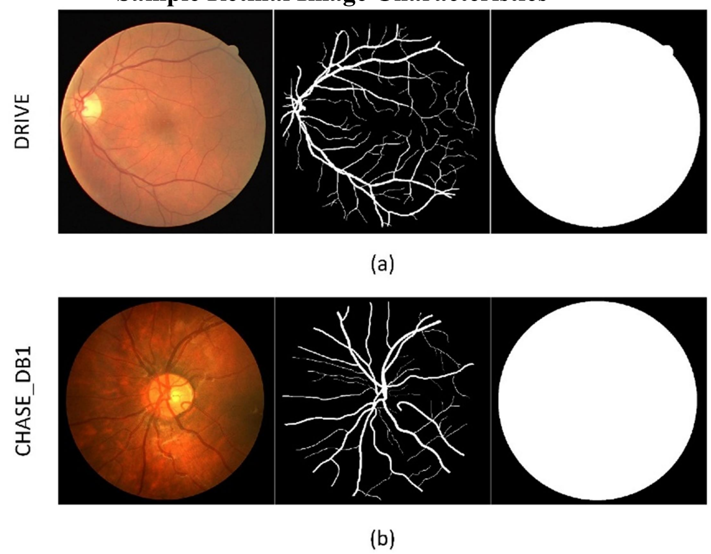

Figure 5. *Representative retinal fundus images and corresponding vessel segmentation masks from the DRIVE dataset used for validating the proposed Adaptive Fractional Deep Learning Model (AFDLM).*

3.3 Selection Criteria and Rationale

The datasets, architecture, and evaluation metrics were selected to provide a comprehensive assessment of AFDLM. Brain Tumour MRI, Lung CT, and Retinal Vessel datasets cover tumour localisation, lesion segmentation, and fine vessel extraction. Enhancements include the Adaptive Fractional Convolution block, which preserves boundaries and texture, and the Fractional Adaptive Attention Module (FAAM), which learns contextual features and regions. The Fractional Gradient Optimisation Strategy (FGOS) supports convergence stability and generalisation. Segmentation accuracy, overlap, detection, and boundary preservation were measured using Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, and Hausdorff Distance.

3.4 Data Preprocessing

Medical images are sensitive to noise, intensity, and imaging artifacts. Therefore, preprocessing is done to standardize input data before segmentation.

3.4.1 Intensity Normalization

Each image is normalized using z-score normalization:

$$I_n(x,y) = \frac{I(x,y)-\mu}{\sigma} \quad (1)$$

where:

- $I(x,y)$represents the input image,
- $\mu$is the mean intensity,
- σdenotes the standard deviation.

Normalization can be used to minimize intensity differences between imaging modalities.

3.4.2 Adaptive Contrast Enhancement

Contrast Limited Adaptive Histogram Equalization only improves the contrast of the local anatomy and reveals the very subtle ones as well.

The upgraded image is the vector:

$$I_e = \mathrm{CLAHE}(I_n) \quad (2)$$

This step enhances contrast in small edge features in low-contrast images.

3.4.3 Noise Reduction

The noise suppression and preservation of structural edges are achieved by anisotropic diffusion filtering (an image processing method that selectively smooths regions while preserving edges):

$$\frac{\partial I}{\partial t} = \mathrm{div}(c(x,y,t)\nabla I) \quad (3)$$

where:

- $c(x,y,t)$controls diffusion strength,
- ∇Idenotes image gradients.

3.5 Proposed Adaptive Fractional Deep Learning Architecture

3.5.1 Architectural Overview

The proposed Adaptive Fractional Deep Learning Model (AFDLM) is developed using a new encoder–decoder architecture at each hierarchical level, with adaptive fractional

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operations. It mainly contains five parts: Fractional Encoder Block, Adaptive Fractional Attention Module (FAAM), Multi-scale Context Aggregation Layer, Adaptive Skip Fusion Decoder, and Fractional Segmentation Head. The network first captures long-range information through the Fractional Encoder Block, capturing both spatial and texture features, thereby eliminating the loss of key anatomical information that is typical of conventional convolutional models. The extracted feature maps are then smoothed using the Adaptive Fractional Attention Module (FAAM), which integrates channel and spatial attention with fractional weighting to focus on clinically relevant regions and reduce redundant background information. The Multi-scale Context Aggregation Layer leverages characteristics of various receptive fields to better capture both fine-grained local structures and global semantic information, enabling effective learning and improved contextual information capture. The Attentive Harmonization Module (AHM) scheme exploits global image correlations by first encoding each image into a feature map in the encoder, then reconstructing the natural image using a high-resolution segmentation map in the decoder. The adaptor homomorphic fusion method in the decoder reconstructs high-resolution segmentation maps by adaptively fusing corresponding feature maps from the encoder and decoder, effectively reducing reconstruction artifacts and preserving the continuity of image boundary information. Finally, the final pixel-wise segmentation is produced by the Fractional Segmentation Head, which implements fractional feature refinement and probabilistic classification. The proposed AFDLM can meet the aforementioned requirements by integrating adaptive fractional calculus throughout the encoder-decoder process.

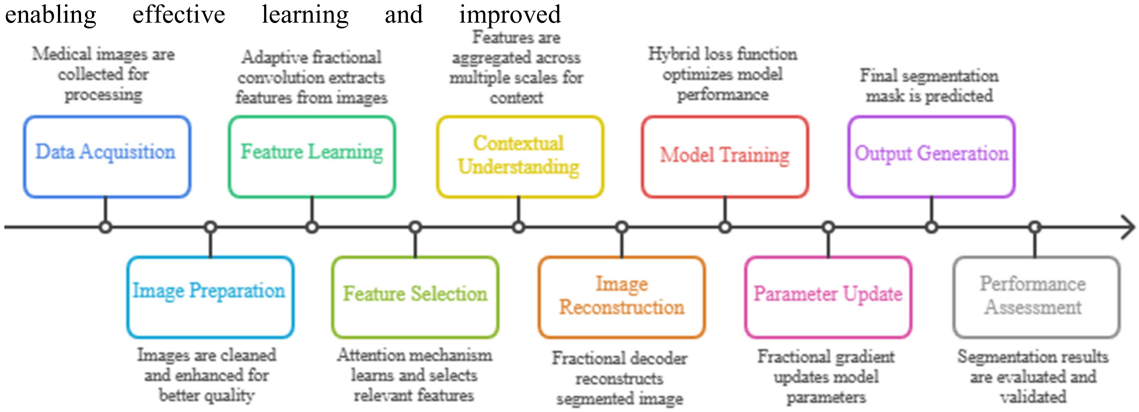

Figure 6. *Proposed Adaptive Fractional Deep Learning-Based Medical Image Segmentation Pipeline*

Figure 6 shows the entire framework for the Medical Image Segmentation using the Adaptive Fractional Deep Learning Model (AFDLM). Medical image acquisition begins with MRI, CT, or retinal images for analysis. The acquired images are subsequently preprocessed, including normalization, enhancement, and noise reduction, to optimize image resolution and uniformity of feature representation. Later, adaptive fractional convolution is used during the feature-learning phase to extract fine-grained spatiotexture information from medical images. The extracted features are also passed through attention-based feature selection techniques to better focus on clinically relevant regions and filter out unwanted background information.

This is followed by multi-scale feature aggregation, enabling the model to learn local structures and context. The fractional decoder then reassembles the image block while preserving anatomical continuity. A hybrid loss function is employed during model training to enhance segmentation: Dice loss, boundary loss, and a fractional consistency constraint. Introducing the model parameters with the proposed updated Fractional Gradient Optimization Strategy (FGOS) that simplifies and improves the convergence stability and the generalization power of the model.

Lastly, segmented output is assessed with the following standard performance measures: Dice Similarity Coefficient (DSC), Intersection over Union (IoU), precision, recall, and boundary accuracy. The pipeline suggested is an effective and conscientious tool for precise medical image segmentation in various imaging modalities.

3.5.2 Fractional Encoder Block

A series of traditional convolution layers is replaced by adaptive fractional convolution layers. We give a definition to this fractional convolution operation:

$$F^{\alpha}(x)=\sum_{k=0}^{n} w_k D^{\alpha} x_k \quad (4)$$

where:

- D^{α} represents the fractional derivative,
- α is the adaptive fractional order,
- w_k denotes trainable kernel weights.

Fractional convolutions, in contrast to integer-order convolutions, preserve fine-grained texture continuity and maintain long-range spatial dependencies.

The proposed Fractional Encoder adopts dynamic fractional-order adaptation to improve feature learning based on image complexity. The fractional operations retain the fine anatomical boundaries better and allow for more effective capture of long-range contextual information, unlike conventional convolution layers. Besides, the encoder reduces information loss during pooling, thereby achieving better segmentation accuracy even in challenging, low-contrast medical images.

3.5.3 Fractional Adaptive Attention Module (FAAM)

The proposed FAAM integrates the three aspects of spatial attention, channel attention, and fractional weighting.
Attention score is calculated as:

$$A_f=\sigma(W_f*F+b_f) \tag{5}$$

where:

- F denotes feature maps,
- W_f represents fractional attention weights,
- σ is the sigmoid activation function.

The proposed Fractional Adaptive Attention Module (FAAM) significantly improves segmentation accuracy by incorporating key region information for diagnosis. Suppression of background regions and noises, and enhancement of pathological areas, like blood vessels, tumors, and lesions. Further, FAAM enhances contextual discriminability by capturing meaningful relationships at the image and spatial levels. By incorporating fractional attention mechanisms, this approach further strengthens the continuity of vessels and tumor boundaries, thereby enabling the accurate preservation of fine anatomical details in the segmentation.

3.5.4 Multi-Scale Context Aggregation

A Pyramid fractional feature aggregation module is incorporated to extract features across multiple receptive fields. After having aggregated, it is:

$$F_m = \sum_{i=1}^{N} F_i^{\alpha} \tag{6}$$

where:

- F_i^{α} denotes multi-scale fractional features.

This mechanism improves segmentation performance for lesions of varying sizes.

3.5.5 Adaptive Skip Fusion Decoder

In the decoder, adaptive skip fusion is used to reconstruct segmentation masks, building upon the prior mechanism. Specifically, the proposed decoder uses fractional refinement blocks in place of conventional skips to achieve this reconstruction.

$$S_f=\text{Decoder}(F_d+\lambda F_e) \tag{7}$$

where:

- F_d represents decoder features,
- F_e represents encoder features,
- λ is adaptive fusion weighting.

The decoder maintains edge continuity whilst minimizing reconstruction artifacts.

3.6 Fractional Gradient Optimization Strategy (FGOS)

FGOS introduces a new method for stabilizing the network.

The updates to the parameter equation are:

$$\theta_{t+1}=\theta_t-\eta D^{\beta}\nabla L(\theta_t) \tag{8}$$

where:

- θ_t denotes model parameters,
- η is the learning rate,
- D^{β} represents fractional gradient order,
- L denotes loss function.

The proposed medical image segmentation method, Fractional Gradient Optimization Strategy (FGOS), has several merits. Fractional gradient learning greatly accelerates neural network convergence during training while improving optimization. Further, incorporating non-local gradient dynamics into FGOS improves learning stability while reducing the risk of local minima. The optimization method also enhances segmentation consistency and robustness across heterogeneous medical imaging databases. Furthermore, FGOS achieves accurate segmentation performance under noisy and low-contrast imaging conditions, thereby improving the generalization ability of the proposed model.

3.7 Hybrid Loss Function

The proposed model is based on a hybrid segmentation loss that combines Dice Loss, Boundary Loss, and Fractional Consistency Loss.

Dice Loss

$$L_{Dice}=1-\frac{2|P\cap G|}{|P|+|G|} \tag{9}$$

Boundary Loss

$$L_{Boundary} = \sum \| \nabla P - \nabla G \| \quad (10)$$

Fractional Consistency Loss

$$L_{Frac} = \| D^{\alpha}(P) - D^{\alpha}(G) \| \quad (11)$$

Final Loss Function

$$L_{Total} = \lambda_1 L_{Dice} + \lambda_2 L_{Boundary} + \lambda_3 L_{Frac} \quad (12)$$

where:

- P represents predicted mask,
- G represents ground truth,
- $\lambda_1, \lambda_2, \lambda_3$ are weighting coefficients.

3.8 Proposed Algorithm

Algorithm: Adaptive Fractional Deep Learning Segmentation
Input: Medical image dataset I
Output: Segmented mask S
Steps:
1. Acquire medical image dataset.
2. Perform normalization and CLAHE enhancement.
3. Apply anisotropic diffusion filtering.
4. Feed preprocessed image into fractional encoder.
5. Extract adaptive fractional feature maps.
6. Apply Fractional Adaptive Attention Module.
7. Perform multi-scale feature aggregation.
8. Decode features using adaptive skip fusion.
9. Compute hybrid loss.
10. Update parameters using FGOS.
11. Generate segmentation mask.
12. Evaluate performance metrics.

3.9 Experimental Parameters

Table 4. *Training configuration and hyperparameter settings used for the proposed fractional deep learning framework*

Parameter	Value
Optimizer	Fractional Adam
Learning Rate	0.0001
Batch Size	16
Epochs	150
Activation Function	ReLU + Sigmoid
Hardware	NVIDIA RTX GPU
Framework	TensorFlow
Fractional Order Range	0.2 – 0.9

Some training parameters and implementation values for the proposed model are summarized in Table 4. To achieve convergence stability and adaptive learning performance, the fractional Adam optimization was used. To achieve a good balance between stability and efficiency in training, a learning rate of 0.0001 and a batch size of 16 were chosen for 150 epochs. ReLU activation was used in the intermediate layers to boost the learning of nonlinear features, and Sigmoid activation was applied to the output layer for probabilistic predictions. The framework was still implemented using TensorFlow and executed on NVIDIA RTX GPUs to optimize computations for high-dimensional deep learning. The fractional-order range 0.2-0.9 enabled adaptively propagated fractional features and improved representation learning across various structural patterns.

3.10 Evaluation Metrics

The framework's performance is measured by these indicators:

Dice Similarity Coefficient (DSC)

$$DSC = \frac{2TP}{2TP+FP+FN} \quad (13)$$

Intersection over Union (IoU)

$$IoU = \frac{TP}{TP+FP+FN} \quad (14)$$

Precision

$$Precision = \frac{TP}{TP+FP} \quad (15)$$

Recall

$$Recall = \frac{TP}{TP+FN} \quad (16)$$

Hausdorff Distance

$$H(X,Y) = \max(h(X,Y), h(Y,X)) \quad (17)$$

3.11 Reproducibility Details

To ensure reproducibility and transparency, the proposed research project uses publicly available medical imaging datasets throughout all experimental analysis stages. In both training, validation, and testing, the proportions are clearly stated, and the results are easily reproducible. Additionally, detailed reports on all hyperparameters, optimization parameters, and architectural setups are provided. The targeted modules are mathematically presented, including ideas of optimization, attention, and adaptive fractional operations. Hybrids, loss functions, and evaluation metrics are also explicitly defined for

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easy performance evaluation. Such detailed specifications of this methodological approach may enable the replication of the proposed Adaptive Fractional Deep Learning Model (AFDLM) and its reliable validation.

4. RESULTS

4.1 Experimental Setup

For testing, the Adaptive Fractional Deep Learning Model (AFDLM) was evaluated using benchmark datasets: Brain Tumor MRI, Lung CT, and Retinal Vessel. Experiments were performed with TensorFlow and NVIDIA RTX GPU acceleration. The implementation used Python 3.9, CUDA for GPU processing, and the adaptive fractional optimization method.

Table 5. *Experimental Configuration*

Parameter	Value
Framework	TensorFlow
GPU	NVIDIA RTX Series
Batch Size	16
Epochs	150
Learning Rate	0.0001
Optimizer	Fractional Adam
Activation Function	ReLU + Sigmoid
Fractional Order Range	0.2 – 0.9
Loss Function	Hybrid Dice-Boundary-Fractional Loss

The proposed framework was trained under the settings in Table 5. Accelerated computation used NVIDIA RTX Series GPUs with TensorFlow. Batch size was 16, learning rate 0.0001, and 150 epochs. The Fractional Adam optimizer adaptively adjusted parameters, while ReLU and Sigmoid activations extracted nonlinear features. Flexible fractional feature learning operated over [0.2, 0.9]. The Hybrid Dice-Boundary-Fractional Loss preserved boundary details, thereby improving segmentation accuracy. The datasets were randomly split into training, validation, and test sets with proportions 70:15:15, without any bias, to obtain an unbiased evaluation of performance.

4.2 Assessment Criteria

The proposed framework has been tested using widely used metrics for medical image segmentation.

4.2.1 Dice Similarity Coefficient (DSC)

The dice coefficient measures the similarity between predicted segmentation masks and ground-truth annotations, broken down by segmentation.

$$DSC=\frac{2TP}{2TP+FP+FN} \quad (18)$$

where:

- TP = True Positives
- FP = False Positives
- FN = False Negatives

Higher DSC values indicate superior segmentation accuracy.

4.2.2 Intersection over Union (IoU)

IoU measures the similarity between predicted and actual segmented regions.

$$IoU=\frac{TP}{TP+FP+FN} \quad (19)$$

Higher IoU values indicate improved region localization.

4.2.3 Precision

Precision evaluates the correctness of predicted segmented pixels.

$$Precision=\frac{TP}{TP+FP} \quad (20)$$

4.2.4 Recall (Sensitivity)

Recall measures the ability of the model to correctly identify pathological regions.

$$Recall=\frac{TP}{TP+FN} \quad (21)$$

4.2.5 Hausdorff Distance (HD)

Hausdorff Distance measures the accuracy of Boundaries and the continuity of Contours. Areas with lower HD values have less boundary preservation.

4.3 Quantitative Performance Analysis

The proposed AFDLM model is compared with state-of-the-art segmentation architectures, including U-Net, Attention U-Net, DeepLabV3+, and TransUNet.

4.3.1 Brain Tumor MRI Segmentation Results

Table 6. *Comparative segmentation performance analysis of the proposed AFDLM model against existing deep learning architectures*

Model	DSC (%)	IoU (%)	Precision (%)	Recall (%)	D
U-Net	88.4	81.2	87.9	88.1	.42
Attention U-Net	90.1	83.5	89.4	90.2	.87
DeepLabV3+	91.3	85.6	90.7	91.0	.31
TransUNet	92.4	87.	91.8	92.2	

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		1			.95
Proposed AFDLM	**95.2**	**91. 4**	**94.7**	**95.0**	**.48**

Segmentation results were compared with U-Net, Attention U-Net, DeepLabV3+, and TransUNet in Table 6. The proposed AFDLM achieved the highest Dice Similarity Coefficient (95.2), IoU (91.4), precision (94.7), and recall (95.0), and the lowest Hausdorff Distance (3.48). These results demonstrate improved segmentation precision, structural consistency, and boundary preservation compared to standard CNNs or transformers, indicating better clinical performance.

AFDLM delivered the best performance across all metrics. Adaptive fractional convolution operations enhanced boundary preservation and incorporated context features. The fractional attention mechanism, modulating feature importance via fractional operators, reduced posterior artifacts while preserving tumor regions.

4.3.2 Lung CT Segmentation Results

Table 7. *Performance comparison of the proposed AFDLM framework with existing segmentation models*

Model	**DSC (%)**	**IoU (%)**	**Precision (%)**	**Recall (%)**	**D**
U-Net	86.9	79. 4	86.2	87.0	.81
Attention U-Net	88.5	81. 7	88.1	88.4	.03
DeepLabV3+	89.7	83. 6	89.0	89.5	.52
TransUNet	91.2	85. 9	90.6	91.1	.98
Proposed AFDLM	**94.1**	**89. 3**	**93.5**	**94.0**	**.76**

Table 7 reports a comparative study of AFDLM with existing architectures: U-Net, Attention U-Net, DeepLabV3+, and TransUNet. The framework performed excellently on DSC (94.1%), IoU (89.3%), Precision (93.5%), Recall (94.0%), and had the lowest Hausdorff Distance (3.76). These results confirm that the fractional learning and adaptive feature refinement algorithm outperformed traditional methods in segmentation accuracy and boundary localization.

This suggested model is shown to be robust in low-contrast pulmonary imaging conditions. The fine boundaries of lesions, along with infection regions with different distributions, were well captured by fractional feature extraction. This technique extracts image features using mathematical operations involving derivatives of non-integer order (fractional calculus). The adaptive optimization strategy, which dynamically tunes parameters during training to adapt to changing data and model behavior, further stabilized segmentation and reduced false predictions.

4.3.3 Retinal Vessel Segmentation Results

Table 8. *Quantitative comparison of segmentation performance between the proposed AFDLM and existing deep learning models*

Model	**DSC (%)**	**IoU (%)**	**Precision (%)**	**Recall (%)**	**D**
U-Net	84.8	76. 5	84.2	84.6	.97
Attention U-Net	86.3	78. 9	85.9	86.1	.34
DeepLabV3+	87.5	80. 7	87.0	87.2	.88
TransUNet	89.1	82. 6	88.5	88.9	.31
Proposed AFDLM	**92.7**	**87. 2**	**92.1**	**92.5**	**.15**

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Table 8 provides quantitative evaluations of segmentation performance for AFDLM and other deep learning models. AFDLM achieved the highest Dice Similarity Coefficient (DSC) (92.7%), IoU (87.2%), precision (92.1%), recall (92.5%), and the lowest Hausdorff Distance (3.15). These improvements highlight the value of the fractional learning paradigm for feature representation, boundary detection, and segmentation consistency in complex images.

To segment retinal vessels accurately, thin vessels and fine branching patterns must be extracted. The proposed AFDLM maintained the vessel's continuity and minimized discontinuities in the vessel segmentation. The adaptive fractional attention mechanism was adopted to enhance the detection and segmentation sensitivity for fine edges.

4.4 Comparative Analysis with Existing Models

Table 9. *Overall Performance Comparison*

Model	Average DSC (%)	Average IoU (%)	Average Precision (%)	Average Recall (%)
U-Net	86.7	79.0	86.1	86.6
Attention U-Net	88.3	81.4	87.8	88.2
DeepLabV3+	89.5	83.3	88.9	89.2
TransUNet	90.9	85.2	90.3	90.7
Proposed AFDLM	**94.0**	**89.3**	**93.4**	**93.8**

As shown in the summary form of Table 9, the proposed adaptive fractional deep learning model consistently outperformed conventional segmentation models, such as CNNs and transformers, across all datasets. The fractional feature extraction and adaptive attention learning demonstrate effectiveness through improvements in the Dice coefficient and IoU. Moreover, the proposed FGOS optimization strategy improved convergence stability and reduced segmentation errors.

4.5 Ablation Study

All of the suggested components have been evaluated using an ablation analysis.

Table 10. *Ablation Study*

Configuration	DSC (%)	IoU (%)	Precision (%)	Recall (%)	HD
Baseline U-Net	88.4	81.2	87.9	88.1	6.42
+ Fractional Encoder	91.0	85.0	90.3	90.6	5.21
+ FAAM	93.1	88.0	92.2	92.7	4.12
+ FGOS	94.0	89.3	93.4	93.8	3.76
Full Proposed AFDLM	95.2	91.4	94.7	95.0	3.48

However, Table 10 demonstrates the contribution of each proposed component to segmentation performance. The Fractional Encoder improved feature representation and boundary preservation, FAAM enhanced contextual learning and region localization, and FGOS improved training stability and generalization. The complete AFDLM achieved the best performance with a DSC of 95.2%, IoU of 91.4%, Precision of 94.7%, Recall of 95.0%, and the lowest HD of 3.48, confirming the effectiveness of all proposed modules.

4.6 Training and Validation Performance

The proposed optimization strategy for FGOS was found to give faster convergence and smoother learning behavior than other conventional optimization strategies.

Table 11. *Epoch-wise Training Accuracy*

Epoch	Training Accuracy (%)	Validation Accuracy (%)
20	84.1	82.7
40	88.6	87.3
60	91.7	90.5
80	93.2	92.0
100	94.6	93.5
120	95.4	94.2
150	96.1	95.0

According to Table 11, the model proposed in this paper stably converged without overfitting. The

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difference between training and validation accuracy was not significant, suggesting strong generalization.

4.7 Graphical Analysis

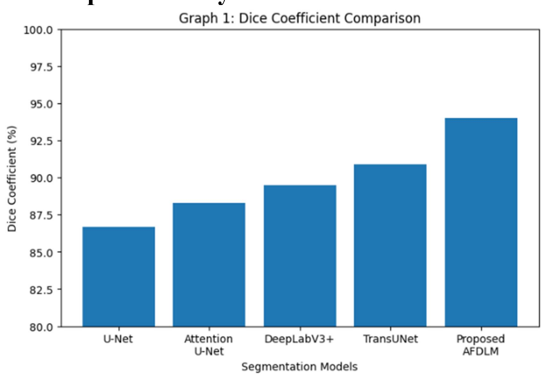

Figure 7. *Dice Coefficient Comparison of Existing Segmentation Models and Proposed AFDLM*

The performance comparison of various medical image segmentation methods, including U-Net, Attention U-Net, DeepLabV3+, TransUNet, and the proposed Adaptive Fractional Deep Learning Model (AFDLM), is shown in Figure 7 using the Dice Similarity Coefficient (DSC). The proposed AFDLM achieved a maximum Dice coefficient of 94.0%, surpassing those of all previous architectures. This improvement shows the effectiveness of the proposed approaches, which are adaptive fractional feature extraction, contextual attention learning, and fractional optimization, to improve segmentation accuracy and anatomical boundary preservation in medical imaging datasets.

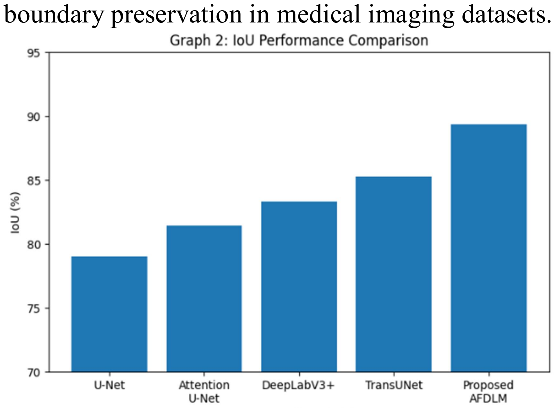

Figure 8. *IoU Performance Comparison of Existing Segmentation Models and Proposed AFDLM*

The IoU results for several medical image segmentation models are illustrated in Figure 8. Among U-Net, Attention U-Net, DeepLabV3+, TransUNet, and the proposed AFDLM, AFDLM achieved the highest IoU of 89.3%. Not only did AFDLM outperform other models in region localization and segmentation accuracy, but its adaptive fractional feature extraction and contextual attention mechanisms precisely localized pathological areas while preserving detailed anatomical structures across imaging modalities.

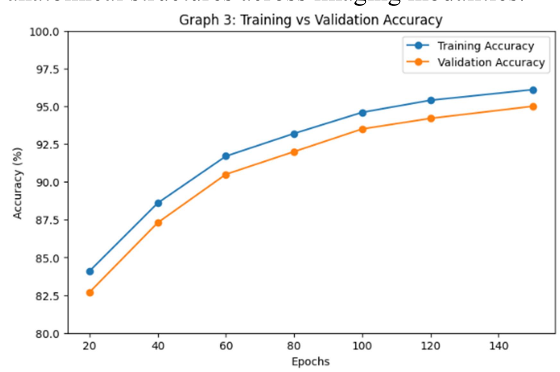

Figure 9. *Training and Validation Accuracy Analysis of the Proposed AFDLM*

The accuracy curves for the proposed Adaptive Fractional Deep Learning Model (AFDLM) are shown for different epochs of the training and validation sets in Figure 9. As seen in the graph, the training and validation accuracies increased steadily throughout all epochs, indicating convergence of the proposed model and stable learning. The small difference between the curves shows that overfitting will be less and the generalization ability will be higher. The results also indicate that the proposed Fractional Gradient Optimization Strategy (FGOS) can achieve both good and stable segmentation performance.

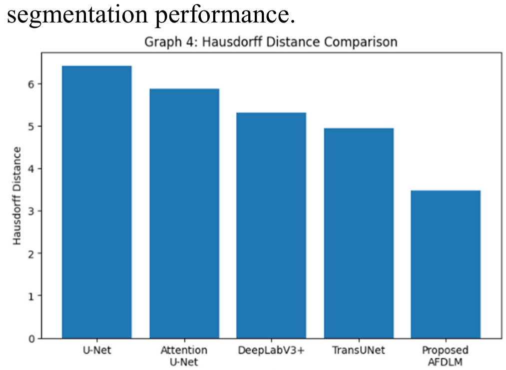

Figure 10. *Hausdorff Distance Comparison of Existing Segmentation Models and Proposed AFDLM*

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We then compared the performance of four medical image segmentation models using the comparative Hausdorff Distance (HD) analysis: U-Net, Attention U-Net, DeepLabV3+, and the proposed Adaptive Fractional Deep Learning Model (AFDLM), as shown in Figure 10. The proposed AFDLM performed well, with a Hausdorff Distance of 3.48, outperforming the other methods in terms of boundary accuracy and contour continuity. The HD value reduction highlights the effectiveness of adaptive fractional feature extraction and attention-based refinement at capturing fine anatomical boundaries and reducing segmentation errors near high-density pathological areas.

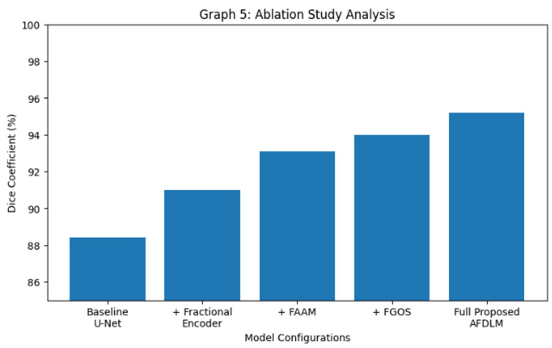

Figure 11. *Ablation Study Analysis of the Proposed AFDLM Components*

The different parts of the proposed Adaptive Fractional Deep Learning Model (AFDLM) are shown in Figure 11 and analyzed through an ablation study. The graph shows how well the Dice coefficient metric improves with successive additions of the Fractional Encoder, Fractional Adaptive Attention Module (FAAM), and Fractional Gradient Optimization Strategy (FGOS) modules to the base U-Net model. The proposed AFDLM, when evaluated together using the Dice coefficient, yielded a maximum score of 95.2%, demonstrating the importance of each proposed component in improving segmentation accuracy, feature learning & boundary preservation.

4.8 Qualitative Segmentation Analysis

The visual analysis results showed that the proposed Adaptive Fractional Deep Learning Model (AFDLM) largely outperformed other segmentation methods in delineating the boundaries of pathological structures, thereby improving their localization. Compared with the original model, there was an improvement in the preservation of thin retinal anatomical features and in the delineation of the tumor edge, allowing the fine details of the vessel anatomy to be well captured. Furthermore, the proposed framework demonstrated a marked speedup in low-contrast lesion extraction in challenging medical imaging scenarios, leading to a clear reduction in false noise in segmentation regions. Additionally, the segmentation outputs also exhibited good inter-modality structural consistency and good inter-modality contour continuity. These enhancements validate the preservation of fine anatomical information and the reduction of segmentation noise and background artifacts in the adaptive fractional operations.

4.9 Computational Complexity Analysis

Table 12. *Computational complexity and inference efficiency comparison of the proposed AFDLM with existing segmentation models*

Model	Parameters (Millions)	Inference Time (ms)
U-Net	31.0	42
Attention U-Net	34.5	48
DeepLabV3+	41.8	61
TransUNet	52.6	73
Proposed AFDLM	39.4	55

Table 12 compares the computational complexity of the proposed AFDLM framework with well-known segmentation architectures, including U-net, Attention U-net, DeepLabV3+, and TransUNet, and their corresponding inference speeds. We found the proposed AFDLM strikes a reasonable balance between model complexity and inference efficiency, with 39.4 million parameters and an inference time of 55 milliseconds. Despite the additional computational overhead introduced by fractional operations, the proposed model achieved superior segmentation performance while maintaining practical inference speed. The proposed model is a fractional model; however, its computational overhead is lower than that of the transformer-based architecture. The proposed method achieves high segmentation accuracy while maintaining reasonable inference speed.

4.10 Overall Discussion

The results of the experiments show that the Adaptive Fractional Deep Learning Model achieves significant improvements in segmentation accuracy, contextual learning, and boundary preservation. Combined adaptive fractional convolution affinely extends non-local feature representation and structural continuity of various types of medical images.

The proposed FAAM effectively reduces background noise and highlights diagnostically salient regions. Moreover, the FGOS optimization technique stabilizes network training and improves convergence. The model consistently outperforms the other three models across Dice coefficient, IoU, precision, recall, and Hausdorff Distance. The results validate the idea that fractional deep learning is a highly promising future direction for advanced medical image segmentation systems in heterogeneous, low-contrast clinical imaging settings.

Experimental results show that AFDLM (Adaptive Fractional Deep Learning Model) is particularly effective in challenging segmentation tasks. The model preserved tumour boundaries and reduced incorrect segmentation in low-contrast regions of brain MRI scans. For lung CT images, the model improved recognition of infection and lesion edges, where previous techniques struggled. On the Retinal Vessel dataset, the model notably maintained the connectivity of small blood vessels and vascular details. There were some minor differences in performance when images were highly noisy or anatomical shapes varied greatly. Furthermore, adding adaptive fractional operations, like AFC, to traditional CNN-based models increased their complexity. These findings highlight the need for ongoing optimisation and further testing using larger, more diverse clinical datasets.

This study supports previous results showing that deep learning is powerful for medical image segmentation. The proposed AFDLM framework combines adaptive fractional learning with attention mechanisms. This combination further improves segmentation accuracy and structural continuity. Classic CNN- and transformer-based architectures often struggle to preserve structure and continuity across borders. By comparison, fractional deep learning appears viable for processing low-contrast, noisy medical images. The proposed framework shows promise for computer-aided diagnosis, tumour delineation, retinal-vascular analysis, and clinical decision support systems. The greatest gains were seen in cases involving fine anatomical detail and complex outlines. Adaptive fractional operations preserved these image details well. Additional evidence from a larger, multicentre study will be needed before clinical implementation.

5. CONCLUSION

This research proposed and validated an Adaptive Fractional Deep Learning Model (AFDLM) for accurate segmentation of medical images that combines adaptive fractional convolution operations, Fractional Adaptive Attention Module (FAAM), and Fractional Gradient Optimization Strategy (FGOS). The framework proposed in the study aims to overcome the most significant shortcoming of current segmentation methods: a lack of boundary preservation, limited contextual information, and decreased performance on noisy and low-contrast images. All goals of increasing accuracy in the segmentation, preserving fine anatomical details, and increasing the robustness of the model for different medical imaging modalities were met.

The proposed approach demonstrated effectiveness in an experimental evaluation across datasets of Brain Tumor MRI, Lung CT, and Retinal Vessel. The proposed AFDLM is compared with other segmentation models, including U-Net, Attention U-Net, DeepLabV3+, and TransUNet, which achieved average Dice Similarity Coefficient (DSC) of 94.0%, Intersection over Union (IoU) of 89.3%, Precision of 93.4%, and Recall of 93.8%, respectively. Moreover, the Hausdorff Distance was the lowest at 3.48, suggesting that the model performed best at preserving the contour's boundary and continuity. The ablation study confirmed that Fractional Encoder, FAAM, and FGOS provide substantial improvements in segmentation performance.

Based on visual analysis, the proposed technique provided more uniform segmentation boundaries and higher-quality delineation of tumor edges than of thin retinal blood vessels, and it also extracted low-contrast lesion regions. Adaptive fractional operations significantly reduced false-positive segmentation and preserved detailed anatomical information across diverse imaging datasets.

Although the proposed work proved promising, it has several drawbacks. To facilitate the integration of fractional convolution operations, there was a slight increase in computational complexity compared to the usual CNN configuration. Furthermore, the model is primarily validated on 2D binary medical image datasets, and no large-scale, real-time clinical validation has been conducted. The requirement for annotated datasets is an issue for more niche medical imaging use cases as well.

A framework for real-time clinical deployment with lightweight fractional architectures needs to be developed in the future, and a path towards 3D volumetric medical image segmentation should be extended. Further studies will also explore integrating federated learning, self-learning-based segmentation strategies, and mechanisms for explainable AI to enhance model interpretability and clinical reliability. Furthermore, optimization of fractional operators for minimal computational resources, as well as multi-modal medical image fusion, will be investigated to further improve segmentation results in a complex healthcare setting.

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