International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-13 Issue-5, June 2024

Enhanced Medical Image Segmentation using Transfer Learning with Res101_UNet: Experimental Insights and Comparative Performance Analysis

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Abstract**:** *Throughout the past few decades, artificial intelligence and machine learning have seen a lot of active research in areas such as computer vision, natural language processing, and speech processing. As a result, deep learning models became state-of-the-art for computer vision tasks such as object detection, classification, segmentation, and other allied tasks. Of course, the fruits of this research are extended to the design of robust and reliable digital health systems as well as other applications in the healthcare sector. Many clinical applications require the automatic segmentation of medical images. Recent deep learning-based approaches have demonstrated state-of-the-art performance in medical image segmentation tasks. In addition to their ability to automatically extract features and generalize over large amounts of data, transfer learning based deep learning models have proven to be handy for data scared areas like medical domains. In this research, we investigate and demonstrate the efficacy of a DCNN-based transfer learning model -Res101_Unet, which has been trained and/or fine-tuned to execute tumor tissue segmentation tasks in MRI, CT, PET, and X-RAY pictures of medical organ scans with little data. For our experimental study, we employed two image datasets: 'Liver Tumor' and 'Gland Colon Cancer', both obtained from the Kaggle portal. This experimental setup includes an Open-Source segmentation model API. Our findings indicate that domain similarity-based transfer learning can be used to data-scarce sectors. We achieved 98.47% accuracy and a IoU score of 0.9891 on Liver Tumor data and 0.6956 accuracy and a IoU score of 0.7043 on gland colon dataset.*

Keywords: Medical Image Segmentation, Deep Learning, Res Unet, DCNN, Transfer learning, Domain Similarity.

I. INTRODUCTION

Over the past few decades, we have witnessed a substantial increase in the development of new imaging modalities and their applications to a variety of clinical and biomedical problems. As a result of the huge progress made in some of these technologies, the development of image-based technologies, as well as their use in new fields of research and clinical practice, is gaining momentum and is expected to continue. Image segmentation is key to applying imaging technology to the treatment of many biomedical problems.

It is often necessary to segment and isolate tissues, cells, and organs from two-dimensional or three-dimensional digital image data to conduct subsequent quantitative analysis in a variety of experimental biological studies and clinical medicine. For example, MRI brain scans can be utilized to quantify gray matter and white matter tissues to study neurological disorders (e.g., Alzheimer's), and images can be used to segment cells and tissues in histopathology images to aid in diagnosing different lesions or to characterize the distribution of different cells and tissues.

Thanks to the vastly improved capabilities of imaging, As a result of recent technological advancements, segmentation

by hand is no longer a viable option for many quantitative studies [5]. The most important part of medical image processing is image segmentation. Image segmentation is a procedure for extracting the region of interest (ROI) through an automatic or semi-automatic process.

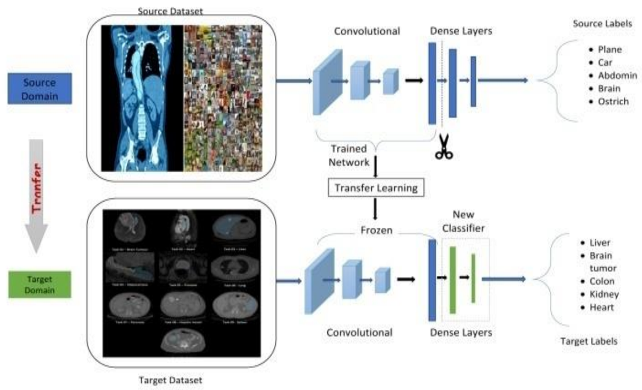

Fig. 1: An Example of Transfer Learning for Medical Image Classification

The deep learning vision algorithms are mostly inspired by human brains. However, they require a huge amount of training examples to learn a new model from scratch and failed to apply knowledge learned from previous domains or tasks [1].

Manuscript received on 27 April 2024 | Revised Manuscript received on 06 May 2024 | Manuscript Accepted on 15 June 2024 | Manuscript published on 30 June 2024.
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State-of-the-art deep learning models have been proposed in the literature for medical image segmentation tasks like Unet [2], Segnet [3], DRINet [4], etc. The models are either task-specific or domain-specific and need huge data for training and evaluation of these models. In most cases, these models cannot be applied directly to data scared image segmentation. There is a need for a system that can perform segmentation tasks with limited data. Researchers have addressed the above problem and discovered that transfer learning-based approaches are good at generalizing segmentation tasks. Describe what transfer learning is in the next section and the use of transfer learning in medical image segmentation and few of the related work done to date.

The remaining paper is organized as follows: Section I overview of transfer learning and its types, Section II summarizes studies that have attempted to predict and address issues related to Image segmentation using Transfer Learning, Section III gives an overview of the methodology adopted by Res101_Unet, Section IV outlines the datasets, Section V describes the experimental setup based on the segmentation models API, Section VI presents the results, and Section VII concludes the paper and Section VIII mentions the acknoledgements.

II. TRANSFER LEARNING

A. What is Transfer Learning?

Transfer learning is an approach that applies knowledge obtained from one problem (Problem S) to solve another problem (Problem T). The basic idea behind transfer learning is that “Learning to segment a scenery image helps a model later to learn more quickly to segment a biomedical image”. Below is a brief summary of various transfer learning methodologies.

Table. 1: Types of Transfer Learning Methodologies

Transfer Learning Approach	Description	Application	Advantage	Disadvantage
Homogeneous Transfer Learning	Same feature and label space.	Image classification, text classification.	Preserves task structure.	Need source and target tasks are should be related.
Heterogeneous Transfer Learning	Different feature or label space.	Object detection, sentiment analysis.	Allows adaptation to diverse tasks.	Requires alignment of different feature spaces.
Instance-based Transfer Learning	Instance-level knowledge transfer.	Domain adaptation, few-shot learning.	Flexibility in adapting to specific instances.	May suffer from domain shift.
Parameter-based Transfer Learning	Reuse parameters for initialization	Fine-tuning pre-trained models, transfer learning in deep neural networks.	Efficient transfer of learned representations.	Prone to forgetting previously learned tasks.
Relational-based Transfer Learning	Capture task relationships for learning.	Multi-task learning, meta-learning.	Encodes inter-task dependencies.	Complex to model relationships accurately.

It is difficult to gather sufficient medical data for training a segmentation model for medical images. Several researchers have applied the state-of-the-art models built on the ImageNet [6] dataset and other publicly available medical datasets to this task, relying on transfer learning. Therefore, the weights of the task-specific models can be used to train the generalized models.

B. Related Work

A de facto Method for deep learning in medical imaging is to transfer data from natural image datasets, especially those in IMAGENET, using pre-trained weights and standard models. *According* to Raghu et al [7], transfer learning benefits large models more than small ones. Wang et al. proposed a cross-tissue/organ segmentation method based on the transfer learning method and a modified deep residual U-Net model, which transferred the knowledge of ultrasound image segmentation from one tissue/organ to another [12].

Transfer learning has shown significant promise in improving biomedical image segmentation models. Studies have demonstrated the effectiveness of transfer learning in enhancing segmentation performance across different medical centers and datasets. By fine-tuning pre-trained models with specific data, transfer learning can adapt deep learning models to new image domains, reducing training time and improving segmentation accuracy [13]. Additionally, the development of Scalable and Transferable U-Net (STU-Net) models has further advanced the field, with parameter sizes ranging from 14 million to 1.4 billion. These large-scale models trained on extensive datasets have shown improved transfer capacities and performance gains in medical image segmentation tasks [13]. The utilization of transfer learning and large-scale models underscores their importance in enhancing the accuracy and efficiency of biomedical image segmentation processes.

Liang et al. conducted a large-scale evaluation on the transferability of models pre-trained on the iNat2021 dataset and 14 top self-supervised ImageNet models on 7 diverse medical tasks in comparison with the supervised ImageNet model and found that fine-grained data and self-supervised models are effective for medical image analysis [14].

Nampalle et al. present a transfer learning-based architecture for medical picture segmentation, with ResNet-110 as the backbone network. To improve segmentation accuracy, the authors apply the Tversky similarity loss function. The proposed system is tested on a variety of medical picture datasets, and the findings reveal that transfer learning greatly enhances segmentation performance [15].

Karimi D et al. investigate the dynamics of model parameters and learned representations in transfer learning-based medical image segmentation. The authors employ a U-Net design using ResNet-50 as its backbone network.

The findings indicate that transfer learning enhances segmentation performance by allowing the model to acquire more robust and generalizable features [16].

Ghavami et al. apply transfer learning to develop a U-Net architecture for biomedical picture segmentation. The authors employ ResNet-50 as the backbone network and test its performance on many biomedical imaging datasets. The results reveal that transfer learning greatly improves segmentation performance over a model built from scratch [17].

Poudel et al. investigate the use of vision-language models (VLMs) for medical picture segmentation using transfer learning. The authors test a U-Net architecture with ResNet-50 as the backbone network on many 2D medical image datasets. The findings indicate that transfer learning from natural to medical images greatly enhances segmentation accuracy, with the extra effect of verbal instructions during finetuning potentially limited [18].

Dorothy Cheng et al. propose a transfer learning-based U-Net architecture for lung ultrasound segmentation. The authors develop the U-Net (V-Unet) using a pre-trained VGG16 model and train it with a grayscale natural salient object dataset (X-Unet). The results reveal that transfer learning greatly improves segmentation performance, while partial-frozen network fine-tuning improves it even more [19][20][21][22][23][24].

These related studies emphasize the importance of transfer learning in medical picture segmentation with ResNet-based architectures. They also demonstrate how transfer learning improves segmentation performance by allowing the model to acquire more robust and generalizable features.

III. METHODOLOGY

The proposed methodology falls under Parameter-based Transfer Learning which includes a deep neural architectural model that is essentially combined with deep 101-layer Resnet [11] for feature extraction and serves as an encoder part, and the *traditional* Unet [2] is used as a decoder part for up sampling the segmented image using the precise spatial information obtained from the encoder part via skip connections. The following figure depicts the transfer learning methodology used in this experimental study.

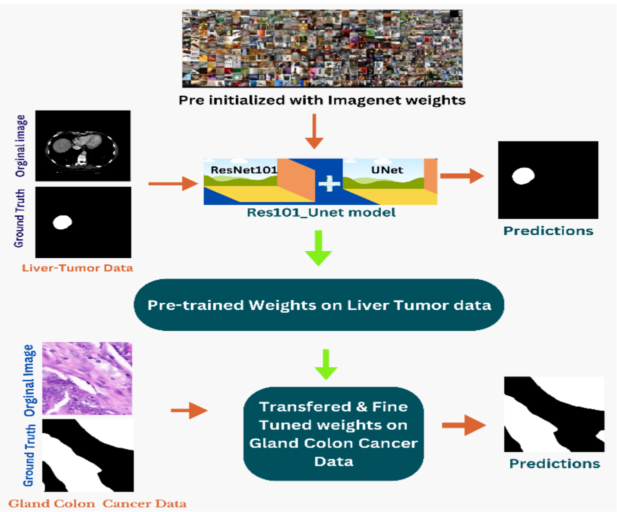

Fig. 2: Process Flow of The Proposed Transfer Learning Methodology

ResNet101 model Description: ResNet-101 is a convolutional neural network (CNN) architecture from the ResNet (Residual Network) family. ResNet-101 is made up of 101 layers, making it deeper than previous versions like ResNet-18, ResNet-34 and ResNet-50 [11]. ResNet models, particularly ResNet-101, are distinguished by their usage of residual connections, also known as skip connections or shortcut connections. These connections let input to travel through one or more layers, allowing the model to learn residual mappings rather than the desired underlying mapping. This helps to mitigate the vanishing gradient problem and makes it easier to train very deep neural networks. ResNet-101 is frequently used for a variety of computer vision applications, such as image classification, object recognition, and segmentation. It has attained cutting-edge performance on a number of benchmark datasets and is widely regarded as one of the most powerful and effective CNN designs.

U-Net model Description: Convolutional neural network architecture U-Net was created specifically for biomedical image segmentation. It is composed of two paths: an expanding path that enables precise localization through up sampling and *convolutional* layers, and a contracting path that gathers context through convolutional and pooling layers. U-Net's symmetric construction makes it possible to train it efficiently on small datasets, which makes it useful for a variety of applications like organ and cell segmentation, lesion detection, satellite image analysis, and industrial inspection.

The following figure displays the model architecture of Res101_Unet.

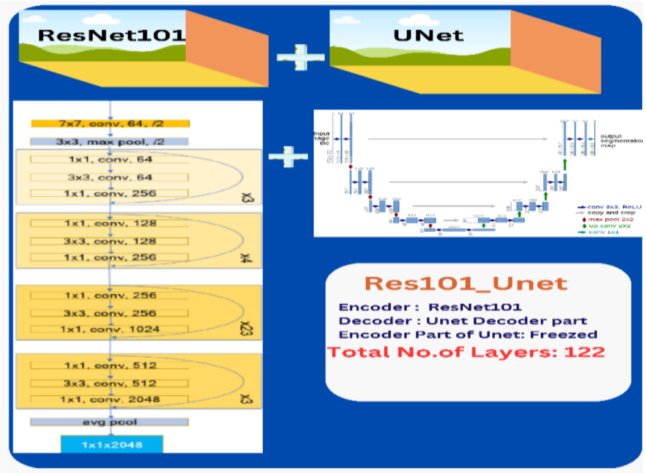

Fig. 3: Architecture of Res101_Unet

Res101_Unet description: A hybrid convolutional neural network architecture called ResNet101-Unet combines the precise segmentation capabilities of the U-Net architecture with the feature extraction capabilities of the ResNet-101 backbone. The vanishing gradient issue is solved by residual connections, and feature maps are up-sampled for a segmentation mask with the same spatial resolution as the input image using a U-Net decoder.

Retrieval Number: 100.1/ijeat.E446013050624
DOI: 10.35940/ijeat.E4460.13050624
Journal Website: www.ijeat.org

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IV. DATASET AND PREPROCESSING

The 3DIRCADB-Liver tumor dataset and the GlaS@MICCAI'2015: Gland Segmentation-Gland-colon cancer dataset, which are both publicly available benchmark medical imaging datasets, were obtained via the Kaggle data science competition hosting portal [8][9][10]. The 2D samples in the collection are included, together with binary masks that isolate the tumor and leave the surrounding area as background. The dataset's attributes are listed in the following table.1.

Table. 2: Overview of the Data

Dataset	Attributes		
	Image Size	Mode	No. of Samples
Liver Tumor	512*512	Grayscale	2058
Gland Colon Cancer	775*522	RGB	85

The following figure shows the sample instances of the datasets used in this study.

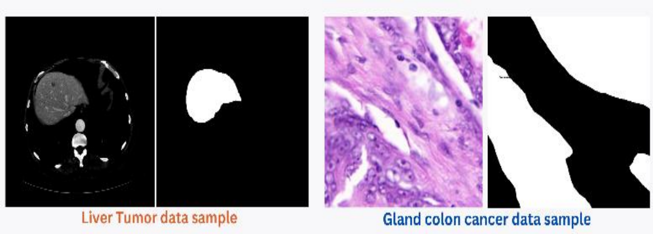
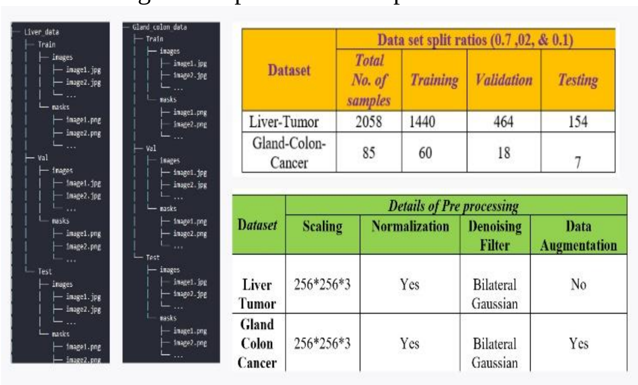


Fig. 4. Dataset Sample Instances and Masks of Liver and Gland Colon Tumors

It is clear that in transfer learning, the knowledge gained during training with a moderately large dataset can be applied to segment the data scared areas, such as gland colon segmentation, where we have very few samples (85), limiting us to do standalone training with the data because deep learning expects more data to perform better. However, our study demonstrates that the application of domain similarity-based transfer learning leverages good results and optimal performance with less data because both the pre-trained dataset and the target dataset belong to the medical imaging domain, and the targets are tumor parts that are mostly similar in shape and texture.

The figure below depicts the dataset folder structure and preparation methods utilized in the experimental study, along with a thorough description of the steps.



Dataset	Data set split ratios (0.7 ,02, & 0.1)			
	Total No. of samples	Training	Validation	Testing
Liver-Tumor	2058	1440	464	154
Gland-Colon-Cancer	85	60	18	7

Dataset	Details of Pre processing			
	Scaling	Normalization	Denoising Filter	Data Augmentation
Liver Tumor	256*256*3	Yes	Bilateral Gaussian	No
Gland Colon Cancer	256*256*3	Yes	Bilateral Gaussian	Yes

Fig. 5: Overview of Dataset Organization, Splitting, and Preprocessing

The Resnet is pre-trained on the ImageNet dataset, which contains color images with dimensions of 256*256. Initially, all images are resized to 256*256 and pixel-wise normalized by dividing each pixel by 255. Both datasets are preprocessed with a Bilateral Gaussian noise filter to perform denoising and improve the clarity of low contrasted medical images, followed by histogram equalization. Data augmentation is only used to the gland colon dataset to enhance the number of samples. The built-in augmentation attributes and standard processes available in the Keras API are used to enrich the data.

V. EXPERMENTAL SETUP

In this study, a Kaggle Notebook with G100 GPU processor and Google Colab's T4 GPU were used as the experimental setup for training, evaluating, and inferring on Res101_Unet. Strong computational resources are required for effective deep learning model training, which is what drove this decision. For quick experimentation, the open-source segmentation models API was used to explore different model structures and setups. To extract features from the liver data, the U-Net model was first trained using various backbone architectures, particularly ResNet. Testing of the ResNet-34 and ResNet-50 backbones yielded results that fell short of the intended performance requirements. As a result, research was conducted on the ResNet-101 backbone, a deep layer neural network with 99 convolutional layers that is regarded as a cutting-edge model for computer vision applications. with a Intersection over Union (IoU) of *0.9891* and training and testing accuracies of 98.25% and 97.60%, respectively, throughout 100 training epochs, this model proved to be exceptionally effective.

Plots were used to show the comparative performance of the ResNet-34 U-Net, ResNet-50 U-Net, and ResNet-101 U-Net models, allowing for a clear grasp of the models' effectiveness. The training parameters were the Adam optimizer, the Binary Cross-Entropy loss function, a learning rate of 0.0001 (1e-4), and 100 epochs.

Following the successful training of the ResNet-101 U-Net model on liver tumor data, the pre-trained weights were used to fine-tune the model on Gland colon cancer dataset. This transfer learning technique produced promising findings, demonstrating its potential use in comparable research situations. The experimental findings section contains a detailed analysis of the results, emphasizing the efficiency of the model and training settings.

The code and implementation can be downloaded from the following: https://github.com/rddvsr/ABMIS-DCNN.git

VI. RESULTS AND DISCUSSION

This section presents and analyzes the qualitative and quantitative findings from our experimental study. Figure.6 compares the qualitative results of Res101_Unet to those of swallow Res_Unets, while Table.3 summarizes the quantitative metrics used to analyze the model's performance. The training, validation, and testing accuracies along with the IoU Score are shown it clearly demonstrate the proposed model's performance.

Retrieval Number: 100.1/ijeat.E446013050624
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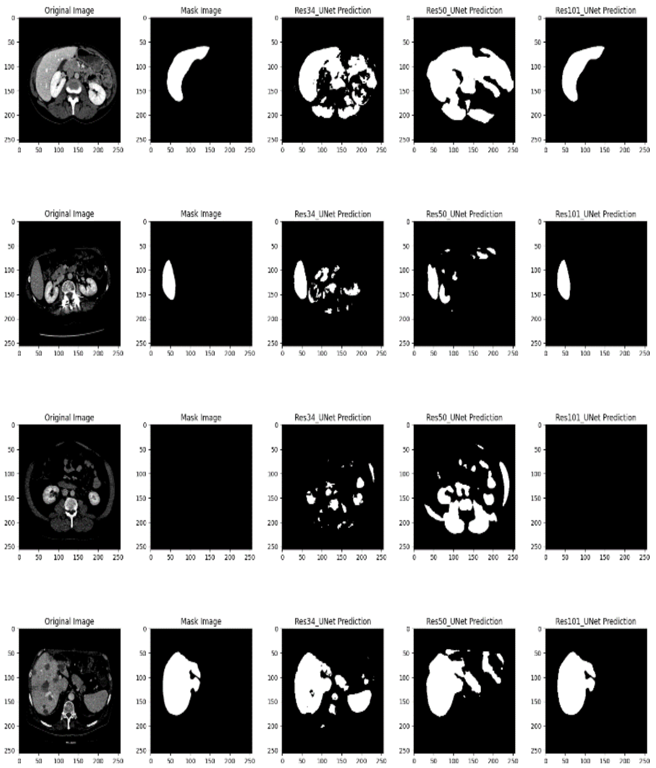

Fig. 6: Comparative Qualitative Predictions of ResNet-101 U-Net and Swallow Res_Unets.

Table. 3: Quantitative results of the Res101_Unet

Data → / Metrics ↓	Liver Tumor data			Gland Colon data		
	Train	**Val**	**Test**	**Train**	**Val**	**Test**
Accuracy	0.9825	0.9829	0.9760	0.6956	0.6559	0.6816
Loss	0.0037	0.0048	0.0098	0.2240	0.4719	0.2880
IoU Score	0.9891	0.9821	0.9724	0.7043	0.6558	0.6780

We have conducted several training trails by changing the various *hyper* parameters for training on the gland colon dataset. We have achieved best results as shown in the Table.3 by applying cross-fold validation with limited data augmentation. The following Table.4 shows the hyper parameters used for the training and fine tuning.

Table. 4: Details of the Hyper Parameters used in the Experimental Study

Data → / Hyper Parameters ↓	Liver Tumor Data	Gland Colon Data
No.of Epochs	100	100
Loss function	Binary_Crossentropy	Binary_Crossentropy
Optimizer	Adam	Adam
Learning Rate	0.00001	0.001
Data Augmentation	No	Yes
Cross-fold verification	No	Yes 5-fold cross validation used

Some of the predictions of Res101_Unet on sample test data is shown below further finetuning can be done to get the better accuracy.

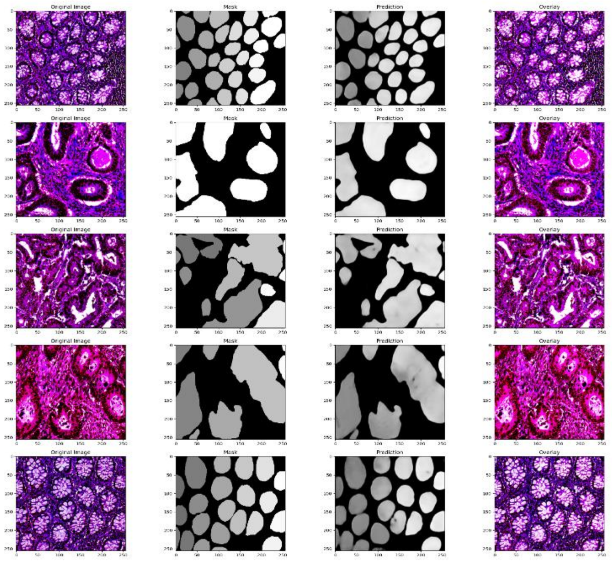

Fig. 7: Comparative Qualitative Predictions of ResNet-101 U-Net on Gland Colon Test Data

VII. CONCLUSION

This work describes a parameter-based transfer learning strategy for medical image segmentation. Our results show that the Res101_Unet model can achieve accurate image segmentation even with limited data availability. Using deep-layer networks allows to extract fine-grained information from the source domain and apply it efficiently to target domains. This capability proves particularly valuable for segmenting tumor sections characterized by diverse forms and sizes. As an extension of this, generic tumor segmentation models can be trained on Res101_Unet using mixed tumor datasets from other organs.

ACKNOWLEDGMENT

We are grateful to the Visvesvaraya Ph.D. scheme, Digital India Corporation, MHRD, India for supporting research through funding.

DECLARATION STATEMENT

Funding	No funding received.
Conflicts of Interest	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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SUPPLEMENTARY DATA

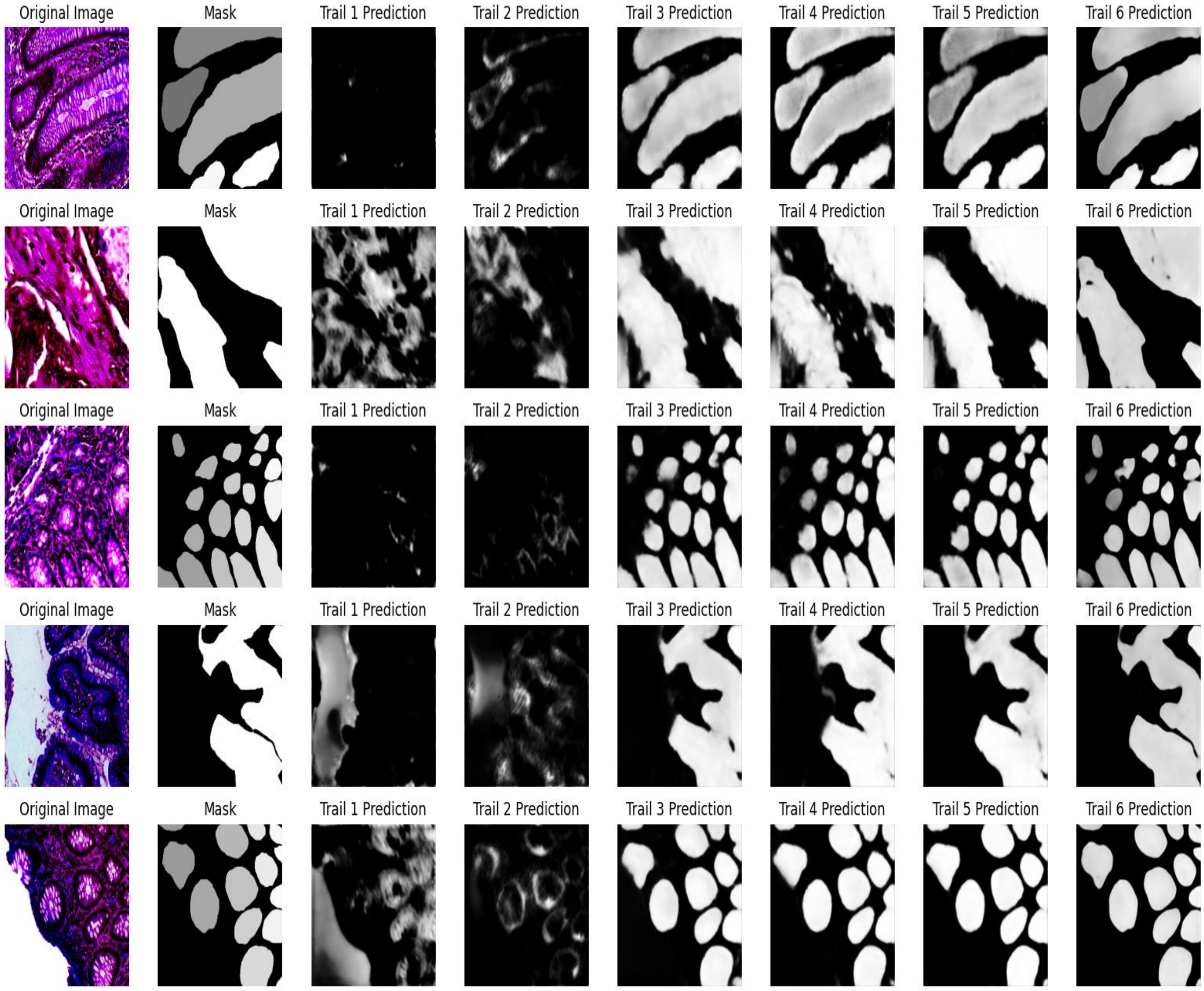

Fig. 8: Comparative Trails Qualitative Predictions of ResNet-101 U-Net on Gland Colon Test data

Retrieval Number: 100.1/ijeat.E446013050624
DOI: [10.35940/ijeat.E4460.13050624](https://doi.org/10.35940/ijeat.E4460.13050624)
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and Sciences Publication (BEIESP)