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Medical Image Segmentation using modified U-Net

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Abstract

Image analysis ranging from lesions to tissues, organs, or entire bodies is central in solving medical issues by pulling out essential data from images acquired through medical imaging facilities so as to enhance odds of an accurate diagnosis. For our model described in this project, we propose a new network structure extending the U-Net model called the Image Contrast-Based U-Net Segmentation model that reframed to diagnose skin diseases by identifying affected areas of the skin. Using red rectangles the model emphasizes the affected areas which is extremely helpful for physicians when diagnoses different types of skin diseases. Through experiments using the ISIC and PH2 datasets, the U-Net model is trained to determine the accuracy above 98% of affected pixels. Also, the specificity of the provided system is the ability to upload test images, as well as to observe the initial and segmented images with marked useful areas and damages. The performance comparison of the two models reveals similar efficiency when working with the two sets of data. The proposed system provides the means for easy identification of skin diseases through simple efficient tools for segmentation of images and can be generalized for improved implementation of medical image segmentation for diagnosis in clinical environments.

*"**Index Terms:** Biomedical imaging, deep learning, neural network architecture, segmentation, U-net".*

INTRODUCTION

Medical image segmentation is acknowledged as one of the key steps in a medical image analysis, which enables to determine the borders of anatomical structures and pathological areas in MRI, CT, and X-ray images. It is a valuable tool in numerous diagnostic and therapeutic approaches, including cancer diagnosis, organ boundary identification, and surgical treatment planning, and makes substantial contribution to refine the medicine and patient individualization, as well as enhancing the therapeutic results [7]. Earlier techniques of segmentation involved drawing contours for different anatomical parts by the physicians or the radiologists themselves, which is not only cumbersome, but also empirical and produces possible inter-observer bias and human errors [8]. Consequently, several approaches for automated segmentation techniques have been proposed for tackling these limitations, and deep learning especially CNN has been observed to be effective because of its potential for learning high level features from raw data [9].

Perhaps, U-Net is one of the most well-known representatives of CNN-based medical image segmentation architectures. Differences in the encoder-decoder neural network organization and skip connections provide an effective way of computing semantics and spatial contextual information necessary to produce accurate segmentation mask [10]. However, for the more complex scenes with high variability and noise, for example, ones observed in clinic, standard configurations of U-Net have exhibited limitations [11]. On these issues, the current research has put forward improvements on the basic U-net architecture that incorporates novel techniques like attention mechanism where the model can direct itself to concentrate certain areas of the image while ignoring the rest of the areas [12]. Furthermore, in order to increase the model robustness and its applicability to a wide range of medical datasets, data augmentation techniques have been applied [13].

The present research intends to work towards creating a new modality of the U-Net model that embeds these advancements: attention mechanisms and Advanced Data Augmentation for boosting segmentation's precision and credibility. It is thought that these improvement will help strengthen the model, benefiting clinical decision making and, in turn, patients [14].

LITERATURE REVIEW

"N. Ibtehaz and M. S. Rahman": Over the last few years deep learning particularly in the medical image segmentation has risen to fame, of which U-Net is the most dominant. Nonetheless, due to an enormous amount of experimental observations, it is becoming apparent that classical U-Net imposes certain restrictions on segmentation of multiple modalities of medical images. To counter these issues, we introduce MultiResUNet [1] which we believe will help better the results of segmentation. Although our modifications were able to give us small improvements in ideal scenarios, the experiments showed substantial performance gains on the difficult datasets which showed relative performance improvement of 10.15%, 5.07%, 2.63%, 1.41%, 0.62% on 5 miscellaneous datasets. Qualitative evaluations shed more light on the positives that MultiResUNet has to do with for which may not be easily explained by quantitative attributes.

"M. Baldeon-Calisto and S. K. Lai-Yuen" [2]: In this paper, we are proposing AdaResU-Net, a Multiobjective Adaptive Convolutional Neural Network for medical image segmentation tasks. This model is formed to flexibly transfer to new datasets with less network size: The paper introduces the U-Net architecture with a residual learning model to promote the information transmission and training speed. For this purpose, we used a multiobjective evolutionary algorithm (MEA) that optimises both segmentation accuracy and model size. AdaResU-Net was compared with U-Net on two medical image datasets that are freely available online and AdaResU-Net was achieved significant improvement with the reduction of training parameters over 70%. However, it may be noted that the MEA could be fairly complicated, hence, may need additional input for fine-tuning and implementation.

"Z. Zhang, C. Wu, S. Coleman, and D. Kerr": In This work, we discuss a new CNN architecture which introduces the Inception-Res module and densely connected convolutional blocks into the existing Model U-net for medical image segmentation. This architecture [3] on the other hand, seeks to extend the depth of the network while solving such problems as gradient vanishing and repeating computations. We tested our model on three challenging segmentation tasks: blood vessel segmentation in the retina imagery, lung division in the CT diagrams, and brain tumor division in the MRI diagrams. The experimental outcome shows enhanced network accuracy with average Dice score of 0.9857, 0.9582 and 0.9867. Nevertheless, the enhanced architectural structure of the new model can bring about the need to optimize the operations carefully and within greater resource demands.

"H. Fu, et.al.," :[4]: In this study, we propose a new medical segmentation approach called Edge-attention guidance Network (ET-Net), based on the representations of edge-attention. In the early encoding layers, there is an edge guidance module to incorporate essential edge information into the network; in the decoding layers, details from the early layers are fused with features of different scales by the weighted aggregation module. To evaluate the effectiveness of our proposed method, we tested it on four segmentation problems: optic disc/cup and vessel segmentation in fundus images, lung contour detection in chest radiography and CT scans. In spite of achieving better performance compared to other methods, their assumption of the edge information may not be effective when contrast or edge definition is low.

[5] "C. Huang, H. Han, et.al.," : To this end, we introduce the 3D Universal U-Net (3D U2-Net) in this paper – a new architecture that is tailored for multi-task medical image segmentation across different organs and imaging paradigms. As for segmentation, while previous methods entail training distinct models for each segmentation task, the 3D U2-Net employs separable convolution to achieve a multi-task learning of domain-specific correlations and commonly associated correlations. The results of experimental testing on five organ segmentation datasets show that the 3D U2-Net provides comparable segmentation accuracy, learning within approximately 1% of the parameters of traditional models. Consequently, invocation of the architecture may require further tune-up to enhance its performance with different tasks.

ALGORITHM

"In this we used algorithms like" –

IMAGE CONTRAST UNET MODEL

This specific U-Net version is called Image Contrast U-Net; it has been developed to target especially medical image segmentation tasks, making use of improvements on contrast to better distinguish the regions affected. This model embraces the boarders of the lesion or diseased areas, making it easy to segment in problematic medical images such as dermal scans. Its architecture is the contracting and expansive paths that comprise the ability to derive fine or grain as well as combinations of features necessary for diagnosis. Used in automated skin disease detection, the model superimposes areas of the skin affected by the disease in order to assist doctors in the diagnosis of skin diseases as well as in improving the processes, efforts and segmentation for diagnosing skin diseases.

ARCHITECTURE

Labeled Image Contrast-Based U-Net Segmentation has a U-Shaped Network Structure and includes contrast image algorithms for, utilizing enhancement techniques to easily identify infected skin regions. The input images are derived from dermatology datasets (ISIC and PH2) which after being passed through the U-Net model yields segmented outputs portrayed with red bounding boxes around diseased areas. An intuitive GUI helps with image upload for visualization of the-original images as well as segmented outcomes, making it easy and accurate to diagnose skin diseases.

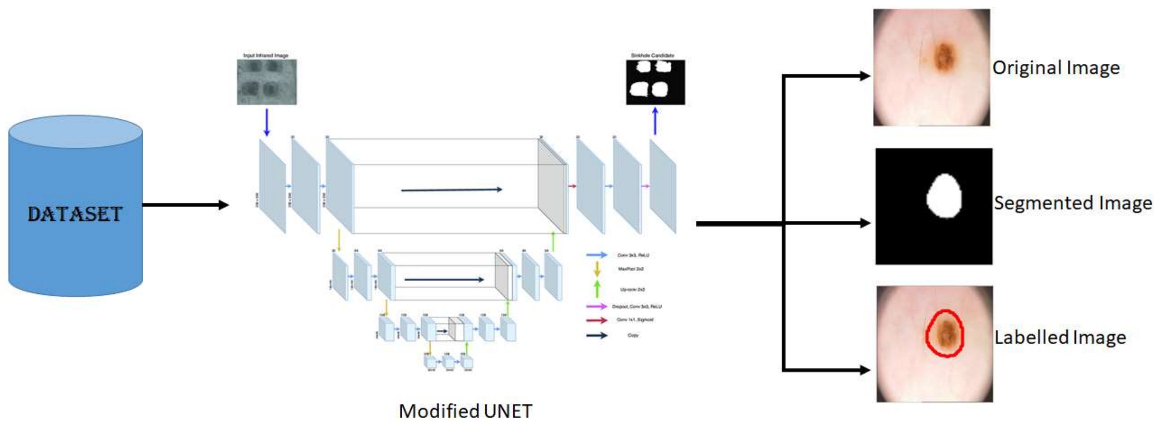

Fig.1: Model architecture

COMPARISON TABLE

Table.1: A summary of Disease Classification Model Based on Multi-Modal Feature Fusion

S.No	Title	Author/Reference	Method/Algorithm implemented	Disadvantage	Advantage
1	MultiResUNet: Rethinking the U-Net architecture for multimodal biomedical image segmentation	N. Ibtehaz and M. S. Rahman [1]	We developed MultiResUNet by modifying the U-Net architecture, incorporating multi-resolution inputs and attention mechanisms to enhance segmentation accuracy on challenging multimodal medical image datasets.	MultiResUNet may require more computational resources and longer training times compared to classical U-Net, potentially limiting its accessibility for smaller research labs with fewer resources.	MultiResUNet significantly improves segmentation performance on complex datasets, demonstrating enhanced qualitative outcomes and providing better generalization across diverse medical imaging challenges compared to the classical U-Net.
2	AdaResU-Net: Multiobjective	M. Baldeon-	AdaResU-Net integrates a fixed U-Net	The complexity of implementing the	AdaResU-Net demonstrates superior

	adaptive convolutional neural network for medical image segmentation	Calisto and S. K. Lai-Yuen [2]	architecture with residual learning, utilizing a multiobjective evolutionary algorithm (MEA) to optimize both segmentation accuracy and network size through adaptive hyperparameter tuning.	MEA may necessitate specialized knowledge, potentially making it challenging for practitioners without deep expertise in evolutionary algorithms and hyperparameter optimization.	segmentation performance while significantly reducing trainable parameters, offering a more efficient solution for medical image segmentation that minimizes computational costs without sacrificing accuracy.
3	DENSE-INception U-Net for medical image segmentation	Z. Zhang, C. Wu, S. Coleman, and D. Kerr [3]	We developed a novel CNN architecture that integrates Inception-Res and Dense-Inception modules within U-Net, incorporating down-sampling and up-sampling blocks to enhance feature extraction and improve segmentation performance.	The complexity of the proposed architecture may lead to longer training times and increased computational requirements, making it less accessible for users with limited resources or computational capabilities.	The proposed model achieves superior segmentation performance on diverse medical imaging tasks, evidenced by high Dice scores, while effectively addressing issues like gradient vanishing and redundant computations in deeper networks.
4	ET-Net: A generic edge-attention guidance network for medical image segmentation	Z. Zhang, H. Fu, H. Dai, J. Shen, Y. Pang, and L. Shao [4]	ET-Net integrates an edge guidance module to capture edge-attention representations in early encoding layers, which are then fused with multi-scale features in decoding layers using a weighted aggregation module.	The performance of ET-Net may be affected in low-contrast images or scenarios with poor edge definition, potentially leading to less accurate segmentations in such conditions.	ET-Net enhances segmentation accuracy by effectively preserving edge information, outperforming state-of-the-art methods across multiple tasks, and demonstrating versatility in various medical imaging applications.
5	3D U2 -Net: A 3D universal U-Net for multi-domain medical image segmentation	C. Huang, H. Han, Q. Yao, S. Zhu, and S. K. Zhou [5]	The 3D U2-Net employs separable convolutions to learn universal representations for multiple medical segmentation tasks, capturing both domain-specific and shared correlations while minimizing additional parameters for each task.	The architecture may require careful tuning for optimal performance when adapting to new domains, and its efficiency might vary based on the complexity of specific segmentation tasks.	3D U2-Net achieves competitive segmentation accuracy with only about 1% of the parameters compared to traditional models, and it seamlessly adapts to new tasks without degrading performance in previously learned domains.

SUMMARY

Recent developments in medical image segmentation highlight the urgent need for improving the existing architecture of neural networks. In the proposed ET-Net, edge-attention representations are incorporated to emphasize the significance of edge information, which contributes to the superiority of the segmentation performance. Likewise, the proposed 3D Universal U-Net also proves the plausibility of one model for solving many of the segmentation tasks with few parameters, outperforming others. However, the Image Contrast-Based U-Net model applies a technique that enhances the disease considering skin areas. Altogether, these papers exemplify novel strategies to improve the use of segmentation methods across a broad spectrum of medical imaging diagnostic processes.

CONCLUSION

A novel and efficient model called Image Contrast-Based U-Net Segmentation is developed to diagnose skin disease by automatically segmenting skin regions in dermatological images. Through evaluating the ISIC and PH2 dataset, the proposed model achieved a high accuracy rate in identifying diseased climates where physicians could easily interpret red bounding boxes. This method of segmentation saves much time and human energy in comparison with the manual study while enhancing the diagnostic accuracy. The variability of the tests achieved with different images shows that the system can indeed be viable for official clinical practice and research. Through the reduction of the number of diagnostic steps and stimulating timely diagnosis, the model upgrades the decision-making capacities of clinicians, which can lead to the patients' better outcomes. The use of a GUI also enhances the interface's ease of use to enhance applicability to clinical settings. In conclusion, the project proves the efficiency of the U-Net-based segmentation in the medical–image analysis, with a focus on dermatological diagnosis as a promising method for the development of new diagnostic tools for skin diseases.

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