Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Medical Image Segmentation Using Modified U-Net

Mohd Mahboob Ali Mahmood[1] , Mohd Sohaib Ali Mahmood[2]

[1]*Chaitanya Bharathi Institute of Technology, alimdmahboob3@gmail.com*
[2]*Keshav Memorial Engineering College, mohdsohaibalimahmood.425@gmail.com*

Medical image analysis is for essential in addressing medical puzzles by extracting respective image information from imaging devices to enhance diagnostic results. The current study proposes an Improved U-Net model named the Image Contrast-Based U-Net Segmentation model used to diagnose the skin diseases, as well as identifying the affected areas of the skin for segmentation. In the developed model, the red boundary box frames the areas affected to assist physicians in the identification and diagnosis of different skin diseases. Both of the used datasets ISIC and PH2 were used for training U-Net model and the test results of the model show that it achieves an accuracy of over 98% for identifying the affected pixels. The above system lets a user to upload test images, view original and segmented images, and the results of the same are clearly marked or highlighted on the areas to be affected. In the lamp-model performance comparison on the two sets of data we find equate performances. The underlying proposed system is an efficient, user friendly tool for skin disease identification which can be extended to other medical image segmentation applications coupled with efficiency increase to the diagnostic workflows in clinical practice.

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

1. INTRODUCTION

Medical image segmentation is an important process in the medical imaging which helps in identifying and locating the structures and abnormalities in all the Imaging modalities like MRI CT scan and X rays. This technique is very useful in various diagnostic and treatment procedures including cancer detection, outlining of internal organs and organs-guide surgery, and has been greatly attributed to the advancement of modern medicine or customised medicine and enhanced health results [34]. Earlier approaches to segmentation were based on manual operations usually done by doctors and are both tedious and still prone to both inter-observer bias and human error[8]. Consequently, numerous attempts have been made to apply automated segmentation techniques that surpassed the above-mentioned limitations; especially deep learning, particularly convolutional neural networks (CNNs) has been found to be effective ways to learn from features that are inherent within data [9].

U-net is another evolutionary CNN based structure intended for medical image segmentation. Due to its encoder-decoder structure with skip connections, it can effectively incorporate both high-to-low level semantic features as well as spatial features, which are important for segmentation [10]. Although it has been successful, there are inherent limitations in the standard U-Net architecture, especially when applied to sophisticated industry-focused datasets displaced with high variance and noise as typically face in clinical practice [11]. To overcome these limitations, there have been researches directing on the improvements of the U-Net structure, some of which involves the application of the attention mechanism, allows the model to pay more attention to the useful portion of the image while ignoring other portions [12]. Furthermore, to enhance the model's performance and the model generalization across different medical data sets, data augmentation strategies have been used [13].

More specifically, this paper's goal is to create a version of the widely used U-Net model that includes these improvements in its architecture and ways of working, such as attention mechanisms, as well as the use of an extensive list of transformations as part of data augmentation processes, in an effort to increase segmentation's precision and dependability. These improvements are expected to increase the compliance of the model, which should lead to more effective clinical decisions, as well as an overall improvement in patient care [14].

2. LITERATURE SURVEY

Medical image segmentation can be viewed as the backbone of medical image analysis since the main objective of medical imaging is to detect or separate structures in the human body pathologies important for diagnostics and treatment. Several approaches based on deep learning have been used to overcome the issues of medical image segmentation, where the U-net as one of the most famous networks. According to Ronneberger et al, the U-shape of U-Net which in addition to comprising of skip connections enables the captures of features at network ends and fine details from the middle of the network that makes it perfect for segmentation problem in medical image [6]. However, several challenges limit the application of traditional U-Net models when applied in new complex medical datasets that are defined by variability in imaging modality and noise.

In this section, some changes that have been made regarding the basic design of U-Net will be discussed. Ibtehaz and Rahman presented MultiResUNet that enhances the fundamental U-Net structure by adding multiresolution blocks to address spatial hierarchies present in multimodal biomedical images, thus increase segmentation capability in range of medical imaging assignments [1]. Furthermore, Baldeon-Calisto and Lai-Yuen have developed a multiobjective adaptive CNN, called AdaResU-Net, which adjusts the convolutional layers with reference the image complexity and improves the network capacity in segmenting different medical images efficiently [2]. Zhang et al. then fine-tuned the architecture and created the DENSE-INception U-Net which improves from the densely connected inception modules, which enables the Network to have better feature extraction and thus better segmentation accuracy [3].

Convolutional features have also been integrated into segmentation models, in order to promote improved attention on the suitable image areas. For example, Zhang et al. proposed ET-Net, which is an edge-attention guidance network that integrates the attention mechanisms and edge detection to improve the segmentation accuracy, primarily concerning to boundaries where most of the segmentation models have difficulties [4]. On a similar note, 3D U2-Net developed by Huang et al. extend the well-known U-Net architecture for 3D application for volumetric medical image segmentation for multi-domain particularly for tasks defining intricate anatomy [12].

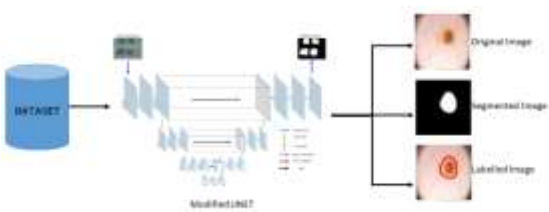
These enhancements show that U-Net has the potential for incorporating more complex approaches, such as multiresolution analysis, or adaptive convolutions, dense connections or attention strategies since it lacks ability of traditional models. Furthermore, Chen et al. presented DRINet, which adopts deep residual learning to enhance segmentation performance in medical images, since deep learning usually suffers a vanishing gradient issue [7]. In combination with each other, these improvements demonstrate the continuous process of optimization of U-Net and other CNN-derived networks for better segmentation performance in a wide range of medical imaging and diseases.

3. METHODOLOGY

a) Proposed Work:

In this project, we present an enhancement of the U-net framework known as the Image Contrast Based U-Net Segmentation model for the segmentation of skin affected regions from the medical images. This model is built to enhance the detection of skin disease areas by utilizing the red bounding boxes that can help physicians diagnose skin diseases. To this aim, the system leverages two extensively used dermatology datasets notably ISIC and PH2, comprised of various skin lesion images. To improve the identification of the affected regions, U-Net model employs methods of image contrast to achieve an accurate segmentation. In this case, an easy to use interface is provided whereby the users can upload test images, apply processing through the model and in the end visualize the images before and after segmentation. The goal of the system is to help clinicians in this process, decreasing the amount of time spent on manual work, increasing the accuracy of the diagnosis and possibly helping to identify skin diseases at an early stage which would lead to an improved care of the patient.

b) System Architecture:



"Fig 1 Proposed Architecture"

Based on this architecture, we propose the following modifications to a U-Net model that will take inputs from dermatology datasets such as ISIC and PH2. The architecture outputs three key images: the original image, the segments of the image showing affected areas and the labeled image where different regions are circumscribed with a red rectangle to enhance the work of clinicians in diagnosing any forms of the disease.

c) Dataset Collection:

The proposed Image Contrast-Based U-Net Segmentation model is trained using two widely recognized dermatology datasets: ISIC and PH2. ISIC dataset is an extensive archive of dermoscopic images of skin lesions involving melanoma, nevus, and seborrheic keratosis available at the International Skin Imaging Collaboration. Another, relatively limited but highly-selected dermoscopy dataset is PH2, which consists of high-quality dermoscopic images of melanocytic lesions with benign, atypical, and melanoma characteristics. These are comprehensive source of skin lesion images which offers the model a wide frame of reference in tackling broad range of skin conditions for accurate segmentation.

d) Modules:

Load Image Contrast UNET Model: To start this, click on the Load Image Contrast UNET Model button to load the U-net segmentation model or more specifically for segmenting the dermopathological images for skin disease.

Upload ISIC Test Image: This shall be used to test the segmentation performance of the U-Net model for skin lesion based on an example in the ISIC datasets "Upload ISIC Test Image" button.

Effected Area Calculation (ISIC): After uploading the ISIC image, you should click the button named "Effected Area Calculation" so that the model can identify the affected skin regions and draw bounding boxes on the corresponding skin areas for better perception.

Upload PH2 Test Image: Go to the segment and click the "Upload PH2 Test Image" button which is another dataset that is used for testing the segmentation result of the model and aims to detect skin diseases more accurately.

Effected Area Calculation (PH2): The next step is to inject the PH2 image and select "Effected Area Calculation" which segments the affected skin components practically skyrocketing the effects as highlighted in the blue color for easier identification of skin disease regions.

ISIC & PH2 Comparison: Press the "ISIC & PH2 Comparison" button, now you can evaluate the performance of U-Net model results on different skin disease image sets in terms of segmentation ability (i.e., it will be much easier to compare the segmentation results of the model on both datasets.).

e) Image Contrast UNET Model:

Image Contrast U-Net: U-Net based architecture for modelling contrast enhancement of medical images, allowing identification of areas most affected. Using contrast of the image, the model enhances the edges of lesions or diseased areas in the image and perform a better Segmentation in complex medical images (for example Dermatology images). The architecture contains contracting paths and expand path that helps to capture both fine grain information and wider context which is particularly important for performing medical diagnosis.

Skin Disease Detection: In automated skin disease detection, it segments skin regions affected with diseases causing skin to be highlighted in images, which helps physicians diagnose skin disease more easily.

By minimizing manual intervention and boosting the accuracy of segmentation, the model improves the overall efficiency of diagnostic workflows in the clinic.

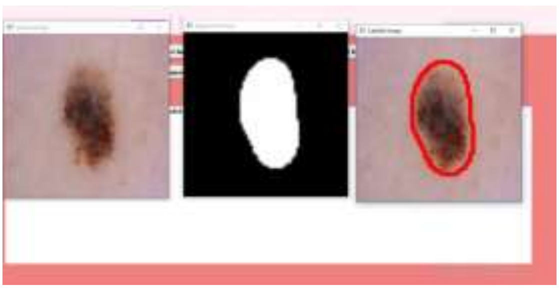
4. EXPERIMENTAL RESULTS

"Fig 2 Comparison Graphs"

"Fig 3 Home Page"

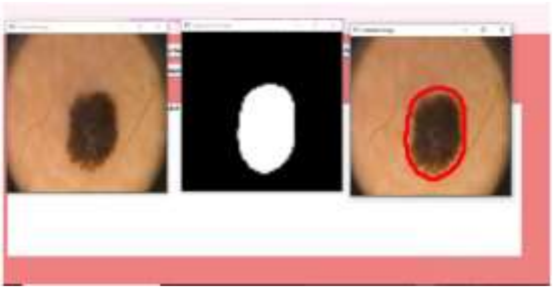
"Fig 4 Load Image Contrast UNET Model"

"Fig 5 Upload Input Image"

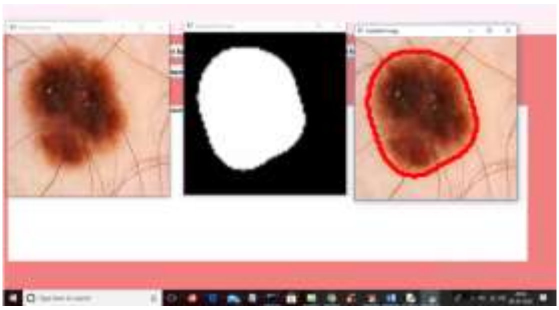


"Fig 6 Output Page"

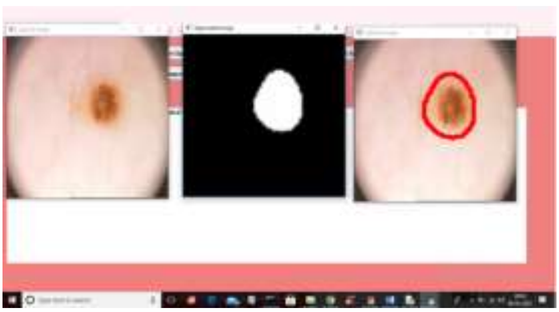
“Fig 7 Upload another Image”



“Fig 8 Output Image”



“Fig 8 Output Image”



“Fig 9 Output Image”

5. CONCLUSION

The developed Segmentaion model Image Contrast-Based U-Net Segmentaion model provides an accurate and labor efficient tool to diagnose skin disease by identifying and segmenting affected areas in a given dermatological image automatically. After training on ISIC and PH2 data-sets the model achieve superior performance in diseased-region visualization over existing approaches where the regions are clearly indicated using red bounding boxes. Such segmentation method greatly minimizes the time and energy devoted to manual analysis while increasing the accuracy of diagnostics. Videos Used in the Study Performance VideosThe ability of the system to receive different test images and report consistent and reliable results across different datasets demonstrates the robustness of our methodology and its potential for practical clinical use. The model streamlines the approach to diagnosis and facilitates early diagnosis, thereby assisting healthcare providers in becoming better decision-makers and thus increasing patient outcomes. The simplicity of the interface also encourages accessibility, and minimum training of end users ensures the integration of the system into clinical workflows. The project overall shows that U-Net based segmentation is an effective technique for medical image analysis, specifically through its application in dermatology, which can be a powerful method for enhanced skin disease diagnosis.

6. FUTURE SCOPE

The project can be extended in future work by including more sophisticated methods like Attention mechanism based on deep learning and more multi-scale features to achieve better segmentation. In addition, the investigation of variety in medical image datasets along with transfer learning can improve the performance of the model across different types of skin diseases. Implementing volumetric skin lesion segmentation through 3D image analysis and expanding the system to detecting other modalities of medical images can make this system more clinically useful.

REFERENCES

[1] N. Ibtehaz and M. S. Rahman, ‘‘MultiResUNet: Rethinking the U-Net architecture for multimodal biomedical image segmentation,’’ Neural Netw., vol. 121, pp. 74–87, Jan. 2020.

[2] M. Baldeon-Calisto and S. K. Lai-Yuen, ‘‘AdaResU-Net: Multiobjective adaptive convolutional neural network for medical image segmentation,’’ Neurocomputing, vol. 392, pp. 325–340, Jun. 2020.

[3] Z. Zhang, C. Wu, S. Coleman, and D. Kerr, ‘‘DENSE-INception U-Net for medical image segmentation,’’ Comput. Methods Programs Biomed., vol. 192, Aug. 2020, Art. no. 105395.

[4] Z. Zhang, H. Fu, H. Dai, J. Shen, Y. Pang, and L. Shao, ‘‘ET-Net: A generic edge-attention guidance network for medical image segmentation,’’ in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., 2019, pp. 442–450.

[5] C. Huang, H. Han, Q. Yao, S. Zhu, and S. K. Zhou, ‘‘3D U2 -Net: A 3D universal U-Net for multi-domain medical image segmentation,’’ in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., 2019, pp. 291–299.

[6] O. Ronneberger, P. Fischer, and T. Brox, ‘‘U-Net: Convolutional networks for biomedical image segmentation,’’ in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., 2015, pp. 234–241.

[7] L. Chen, P. Bentley, K. Mori, K. Misawa, M. Fujiwara, and D. Rueckert, ‘‘DRINet for medical image segmentation,’’ IEEE Trans. Med. Imag., vol. 37, no. 11, pp. 2453–2462, Nov. 2018.

[8] M.Z. Alom, M. Hasan, C. Yakopcic, T. M. Taha, and V. K. Asari, ‘‘Recurrent residual convolutional neural network based on U-Net (R2U-Net) for medical image segmentation,’’ 2018, arXiv:1802.06955. [Online]. Available: http://arxiv.org/abs/1802.06955

[9] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, ‘‘UNet++: A nested U-Net architecture for medical image segmentation,’’ in Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support. Cham, Switzerland: Springer, 2018, pp. 3–11.

[10] Y. Xue, T. Xu, H. Zhang, L. R. Long, and X. Huang, ‘‘SegAN: Adversarial network with multi-scale l1 loss for medical image segmentation,’’ Neuroinformatics, vol. 16, nos. 3–4, pp. 383–392, Oct. 2018.
[11] B. Murugesan, K. Sarveswaran, S. M. Shankaranarayana, K. Ram, J. Joseph, and M. Sivaprakasam, ‘‘Psi-Net: Shape and boundary aware joint multi-task deep network for medical image segmentation,’’ in Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2019, pp. 7223–7226.
[12] J. Wei, Y. Xia, and Y. Zhang, ‘‘M3Net: A multi-model, multi-size, and multi-view deep neural network for brain magnetic resonance image segmentation,’’ Pattern Recognit., vol. 91, pp. 366–378, Jul. 2019.
[13] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and D. Terzopoulos, ‘‘Image segmentation using deep learning: A survey,’’ Apr. 2020, arXiv:2001.05566. Accessed: Jun. 08, 2020. [Online]. Available: http://arxiv.org/abs/2001.05566
[14] V. Badrinarayanan, A. Kendall, and R. Cipolla, ‘‘SegNet: A deep convolutional encoder-decoder architecture for image segmentation,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 12, pp. 2481–2495, Dec. 2017.