MR U-NET BASED IMAGE SEGMENTATION OF SKIN LESION USING DERMOSCOPIC IMAGES

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Abstract-

Skin cancer comes in many different forms, including skin lesions. Melanoma is the primary focus of this paper among the various kinds of skin cancer. When this type of cancer is detected at an early stage, it is treatable. A computer-aided recognition is necessary for the earlier diagnosis. The standard image segmentation methods are used in a variety of computer-aided recognition techniques that are now accessible. In this research, we suggested a new image segmentation approach called the MR U-Net model. We will separate melanoma tumors out of the dermoscopic images using this technique. In the system that is being presented, deep learning is also used. This allows us to initially train the systems with just a handful of datasets and then test it with an extensive amount of datasets. The system's effectiveness is assessed based on the following factors, including detection accuracy and system accuracy.

Keywords- skin lesion, image segmentatin, deep learning, CNN, U-Net segmentation model, CAA.

I. INTRODUCTION

A lesion of the skin is a type of cancer and is made up of several abnormal skin growths. There are many distinct kinds of cancer of the skin that can exist. We just take melanoma cancer into account. Malignant melanoma is another name for this melanoma. This dangerous type of skin cancer is called malignant melanoma. When detected at the earliest possible stage, this form of cancer called melanoma is treatable. The dermoscopy, which is the technique used to spot melanoma in its early stages. Dermoscopic pictures are employed for melanoma analysis. The skin damaged by the melanoma is clearly visible in Fig. 1. There are two methods for doing analyses: manual analysis

and computer-assisted analysis.

Fig.1. Melanoma Affected Skin

Dermatologists are needed for the manual examination process, yet for them it is a challenging and time-consuming task. In the computer-assisted analysis, the dermoscopic images are automatically analyzed and the melanoma-affected region is separated from them. The computer-aided analysis uses methods of image segmentation to separate the melanoma-affected area from the provided dermoscopic image, which is based on the fundamentals of image processing[1].

picture processing is the process of performing specific tasks on a picture. As a result, it raises the image's quality and aids in the extraction of certain pertinent data in that image. The phases of image processing are depicted in fig. 2 in various stages.

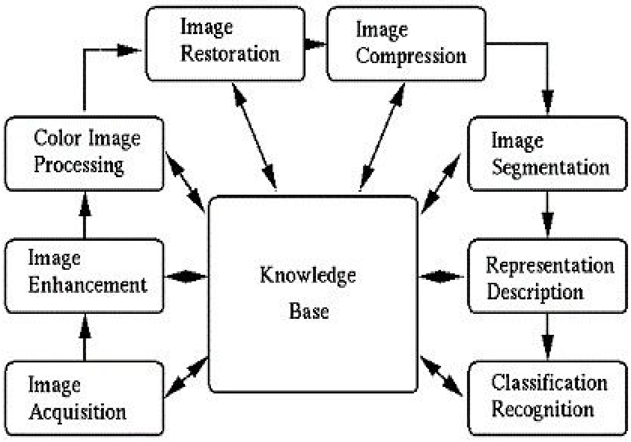

Fig.2. Stages of Image processing

The process of separating the melanoma-affected portion of a particular dermoscopic picture of the skin from the normal zone is known as melanoma image partition. The available image segmentation methods are shown in fig. 3.

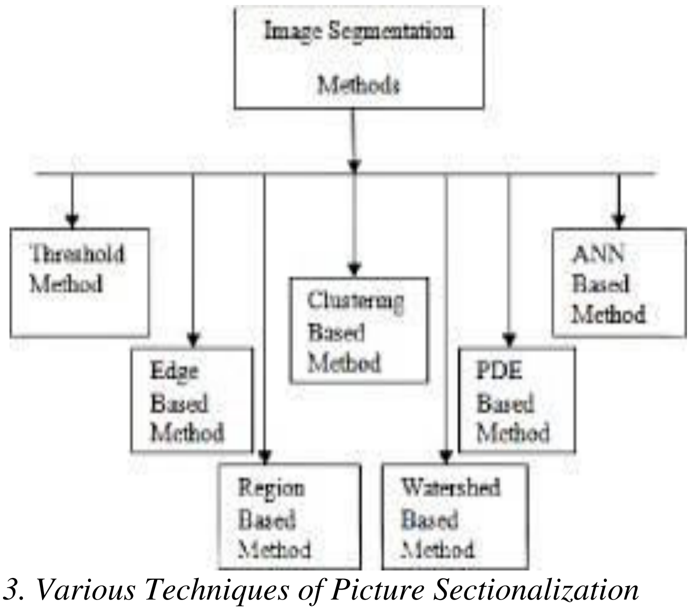

Fig.3. Various Techniques of Picture Sectionalization

Convolutional neural networks (CNN) are among the most widely used techniques for processing images. Image classification, object detection, and other applications of CNN are some of them[7].

U-Net is the type of neural networks structure used. The primary function of the U-Net is to segment medical images. The neural network is known as U-Net due of its symmetrical design. Additionally, it differs from every other FCN variation [8].

A technique known as deep learning is used to train a system to think like a typical human being and to come to its own conclusions. With the use of the deep learning method, the gadget can execute picture categorization tasks immediately from analysis of the image [9].

II. REVIEW OF LITERATURE

The methodology utilized in those papers serves as the foundation for the literature review for the proposed system.

A brand-new method called as the C-UNet image segmentation framework was suggested by Junyan Wu et al. He suggested using the provided dermoscopic pictures to segment the malignant melanoma afflicted region from its normal portion.

The discussion of the present status of automated and semi-automatic methods for achieving separation of problematic medical pictures by Dung L. et al. Fam. Throttling, region growth, clustering, classifiers, artificial neural network models and Markov randomized field models, are currently used techniques for categorizing 2D medical pictures.

A brand-new method of picture segmentation called the fully convolution network (FCN) was proposed by Long j et al. He suggested using this method to automatically segment the provided medical photos.

Exposure to the Design and Results from the Multimodal Brain Tumor Image Segmentation Benchmark- (BRATS), conducted in connection to the MICCAI 2012 & 2013 conference, a pair of cutting-edge tumor segmentation algorithms by BJern H. Menze.et al. A novel method referred to as Pyramid Scene Parsing Network- (PSR Net) was proposed by Zhao h et al. He suggested using this method to divide up the medical imaging.

III. EXISTING SYSTEM

The current method has a better version of the conventional dermoscopic image analysis procedure for melanoma detection. They have suggested a method for segmenting skin lesions in this current system utilizing a deep learning model called C-UNet. It combines innovations like the convolution block & the expanded convolutional layer in the C-UNet.

They have improved the suggested C-UNet image segmentation method by incorporating common entropy loss. Utilizing the conditional random field, additional smooth predicated label mappings were created[1].

IV. PROPOSED SYSTEM

Below are the categories that are split up based on the fundamentals of the job done in our suggested system.

a) Execution of fundamental models
b) Performing dermoscopic image processing

c) Introducing a segmentation model to the system
d) System performance evaluation
e) System cross validation

A. *Execution of basic models*

To comprehend how well the algorithm performs and its flaws, basic methods for image segmentation are put to use in this session.

The approach that is suggested in the current system is used in this module. It is carried out via the U-Net model. By using this strategy, one can gain an understanding of how it is used and any drawbacks it may have[1].

The left side of a U-Net-based partition is a paved path, and its right side is a contract path. It consists of a continuous 3x3 convolution filtration systems, followed by superb 2x2 max pooling and Two stride for downstream sampling[1].

B. *Preprocessing the dermoscopic images*

The major goal of the research is to locate the area of the skin's dermoscopic image that has melanoma.

The image must be resized and its brightness must be increased as part of the preparation stages. The image has to be resized because different sources provided different image databases, which might not all have the identical size.

The dermoscopic pictures are in gray scale, thus there is less intensity in them, which is why the contrast of the picture needs to be increased. By doing this, the image's intensity can be raised.

C. *Training the system with segmentation model*

The suggested MR U-Net images sectionalization models must be trained into the system before it can execute the identification and segmentation operation. The structure of the suggested MR U-Net images sectionalization system is shown in Fig. 4.

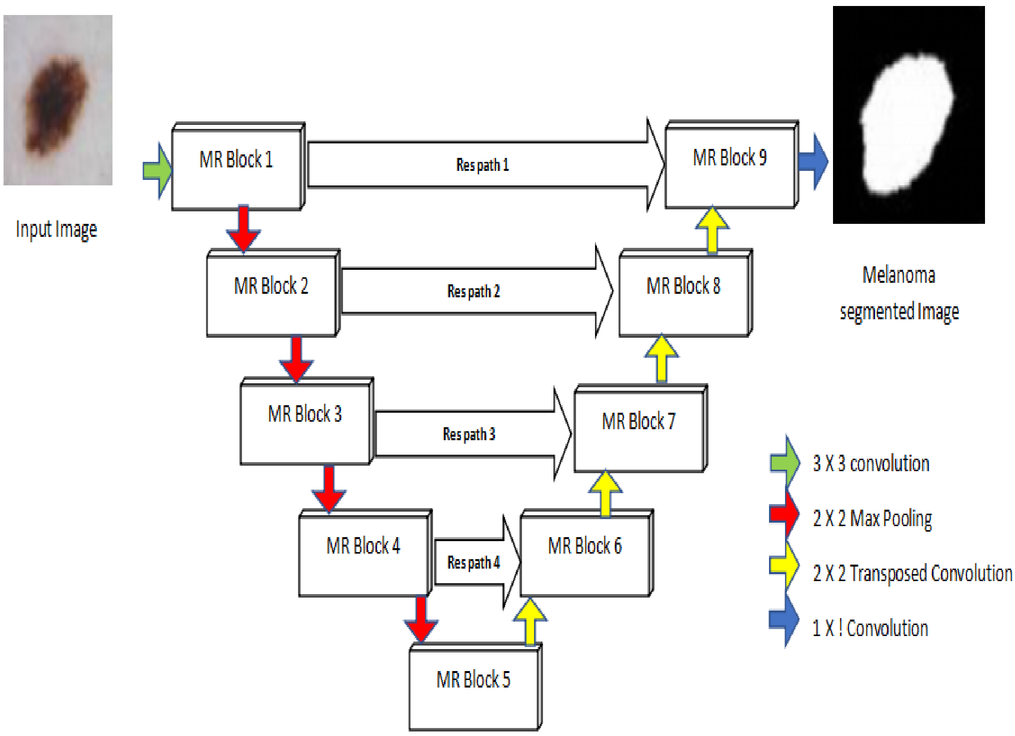

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Fig 4. Architecture of MR U-Net sectionalization model

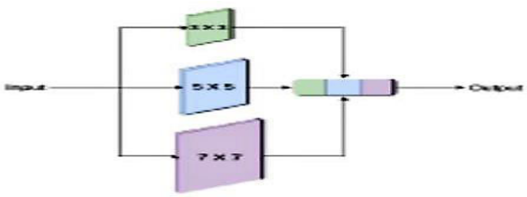
The suggested MR U-Net paradigm differs from the current U-Net model in the ways listed below.
1) A MR block was recommended in place of the two convolution layers.
2) Suggested a Res path in place of the simple short path.

1. *MR Block*

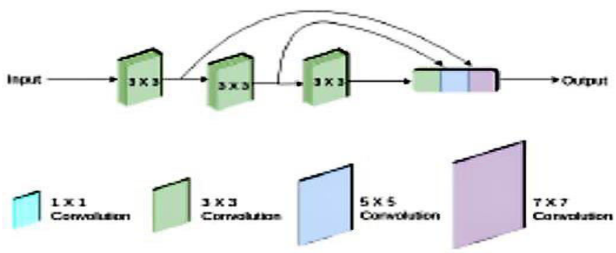
Multi Res Block is referred by the term MR Block throughout the proposed system. The first step in creating the MR Block is to arrange the 3x3, 5x5, & 7x7 filters in parallel. The 5x5 & 7x7 filter are larger and more expensive when compared to 3x3 filters. They are also larger in size. The MR Block's early development is depicted in fig. 5(a).

The 5x5 & 7x7 filters are changed by the 3x3 filters themselves in the following phase. The parallel form has transformed into the serial form on its own. The second phase of the creation of the Magnetic Resonance Block is depicted in fig. 5(b).

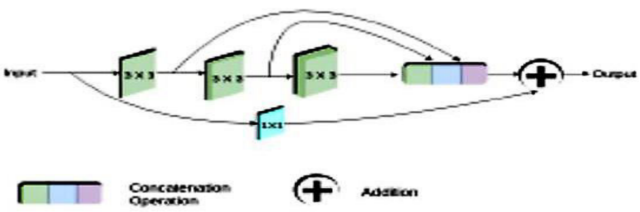
In the last step of the MR Block's development, an additional 1x1 filter is decided along with it, and an adder operation is performed using three 3x3 parallel filters with a 1x1 filter. Understanding some spatial information is made easier by the addition of this 1x1 filter. The multi-res block's final development is depicted in Fig. 5(c). Comparing the Multi Res blocks to the current system, which employs U-Net for the detection process, the precision in the identification and segmentation of a melanoma on the dermoscopic images of the epidermis will be higher.



(a)



(b)



(c)

Fig.5 Developing the Proposed MR Block

2. *Res Path*

The res route is a different method for directly transferring the attributes of an encoder to those of a decoder. The encoder's properties will pass through a variety of mixed filters on the res path before arriving at the decoder's properties, where they will obtain a more accurate result because, in contrast to the direct path, the res path contains filters, allowing it to do so.

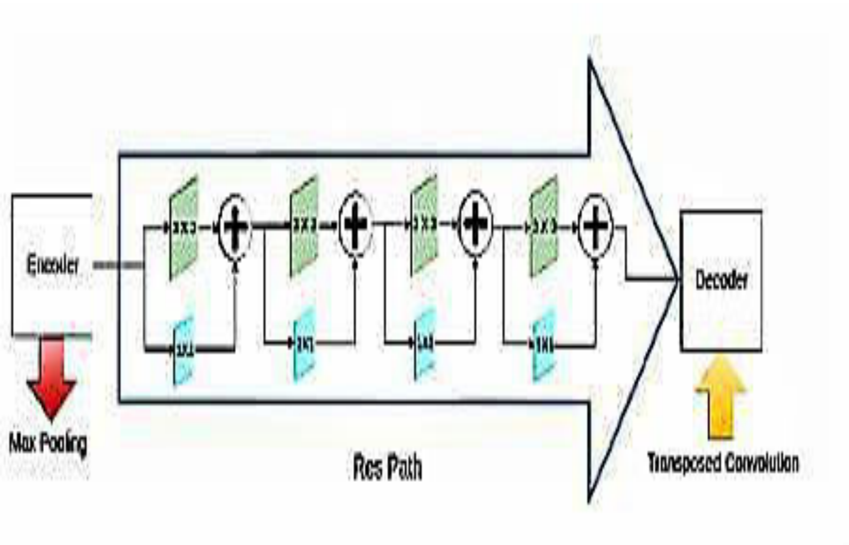


Fig.6 Proposed Res Path

D. *Evaluating the system performance*

The accuracy of the system and the detection accuracy are two metrics used to assess the separation of melanoma utilizing dermoscopic pictures.

$$System\_accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Detection\_accuracy = 2X \frac{precisionX\ recall}{precisionX\ recall}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + TN}$$

$$TP -> True\_Positive$$

$$TN -> True\_Negative$$

$$FP -> False\_Positive$$

$$FN -> False\_Negative$$

E. *System cross validation*

The generated system is cross-validated in the module using several alternative datasets. In this module, the k-means cross validation approach is utilized. The dataset D in this case has been broken down into Y subsets that are which are D1, D2, D3,..., Dy

V. RESULT AND DISCUSSION

The input data for this system proposal is saved within the dermoscopic inputs folder and is given as a dataset of dermoscopic skin images. The images of the melanoma that have been discovered are kept in the dermoscopic outputs folder after the melanoma has been segmented. Figure 7 displays the analysis's findings, including a comparison of the proposed and existing systems' performance as well as a comparison of the systems' accuracy. When compared to the present system, the suggested system's output appears to be identical. Indeed, the results of the current system and the suggested system differ, thus the modifications may not be immediately apparent to us.

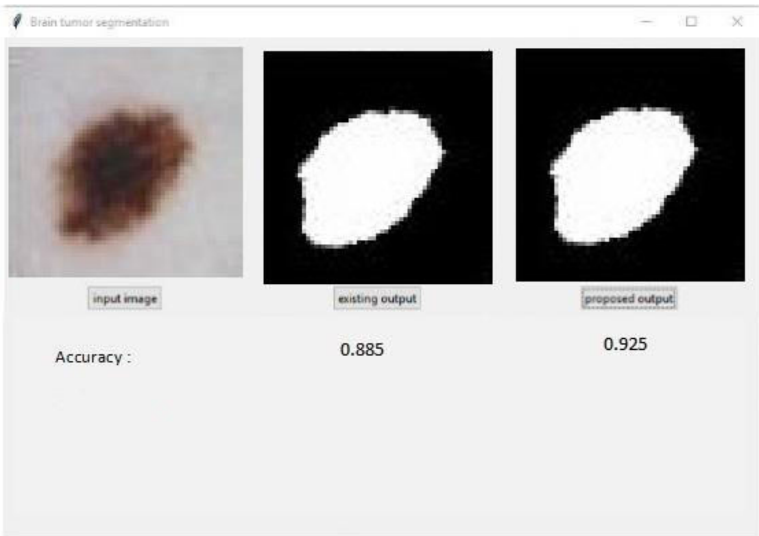


Fig7 Result of the Proposed system

VI. CONCLUSION

In order to segment the dermoscopic images, the suggested system first analyzes multiple segmentation of images techniques. Additionally, some of the drawbacks of various algorithms are examined.

The method entails gathering dermoscopic skin images from multiple sources and performing some preprocessing processes. Thus, from the provided dermoscopic pictures of the skin, melanoma is diagnosed using the MR U-Net segmentation of images technique.

The analysis compares the results of the system that is suggested and the current system using one image that was used to diagnose melanoma. The proposed system's obtained level of system accuracy is 0.925 (92.5%).

This strategy for detecting the different types of skin cancer can improve the proposed system's future performance.The suggested system has applications in the medical industry since it can be used for computer-aided analysis (CAA). The task of the doctor is lessened by this CAA.

REFERENCES

[1] Alom, Md Zahangir, Mahmudul Hasan, Chris Yakopcic, Tarek M. Taha, and Vijayan K. Asari. "Recurrent residual convolutional neural network based on u-net (r2u-net) for medical image segmentation." *arXiv preprint arXiv:1802.06955* (2018).

[2] Codella, Noel CF, Q-B. Nguyen, Sharath Pankanti, David A. Gutman, Brian Helba, Allan C. Halpern, and John R. Smith. "Deep learning ensembles for melanoma recognition in dermoscopy images." *IBM Journal of Research and Development* 61, no. 4/5 (2017): 5-1.

[3] Jiang, Hongda, Ruichen Rong, Junyan Wu, Xiaoxiao Li, Xu Dong, and Eric Z. Chen. "Skin lesion segmentation with improved C-UNet networks." *BioRxiv* (2018): 382549.

[4] Maia, Kenia Regina Oliveira, Graça Maria de Castro Viana, Marcos Antonio Custódio Neto da Silva, Maria do Desterro Soares Brandão Nascimento, Victor Lima de Souza, and Silvio Gomes Monteiro. "Resistant tuberculosis in Maranhão, Brazil: a case series." *BMC Research Notes* 9, no. 1 (2016): 1-3.

[5] Moeskops, Pim, Jelmer M. Wolterink, Bas HM Van Der Velden, Kenneth GA Gilhuijs, Tim Leiner, Max A. Viergever, and Ivana Išgum. "Deep learning for multi-task medical image segmentation in multiple modalities." In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19*, pp. 478-486. Springer International Publishing, 2016.

[6] Razzak, Muhammad Imran, Saeeda Naz, and Ahmad Zaib. "Deep learning for medical image processing: Overview, challenges and the future." *Classification in BioApps: Automation of Decision Making* (2018): 323-350.

[7] Sun, Weiwei, and Ruisheng Wang. "Fully convolutional networks for semantic segmentation of very high resolution remotely sensed images combined with DSM." *IEEE Geoscience and Remote Sensing Letters* 15, no. 3 (2018): 474-478.

[8] Wahab, Noorul, Asifullah Khan, and Yeon Soo Lee. "Two-phase deep convolutional neural network for reducing class skewness in histopathological images based breast cancer detection." *Computers in biology and medicine* 85 (2017): 86-97.

[9] Yu, Lequan, Hao Chen, Qi Dou, Jing Qin, and Pheng-Ann Heng. "Automated melanoma recognition in dermoscopy images via very deep residual networks." *IEEE transactions on medical imaging* 36, no. 4 (2016): 994-1004.

[10] Yuan, Yading, Ming Chao, and Yeh-Chi Lo. "Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance." *IEEE transactions on medical imaging* 36, no. 9 (2017): 1876-1886.

[11] Zhao, Hengshuang, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. "Pyramid scene parsing network." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2881-2890. 2017.