An efficient approach for Skin Lesion Segmentation using Dermoscopic Images: A Deep Learning Approach

Kishore Babu Nampalle[0000−0001−6561−9013] and
Balasubramanian Raman[0000−0001−6277−6267]

Computer Science and Engineering Department
Indian Institute of Technology Roorkee, India
{kbabu89,bala}@cs.iitr.ac.in

Abstract. Segmentation is a process of detecting boundaries of an object to extract the object of interest within a given image. There are different techniques like CT scan, MRI scan, X-ray scan, and so on those can be used to get these medical images. Processing of these medical images is laborious because of variation in size and shape, and contrast. Hence, Skin lesion segmentation became a challenging task for researchers and dermatologists. The Segmentation of medical images plays a vital role in medical diagnosis and further treatment. Although there are many proposed image segmentation techniques, there is no perfect segmentation method that supports different datasets. This paper presents an efficient skin lesion segmentation model using a Convolutional Deconvolutional Neural Networks (CDNN). The proposed framework is developed based on Convolutional Neural Networks (CNN) by replacing the classification network with a segmentation network. The proposed model has used International Skin Imaging Collaboration (ISIC) 2017 challenging data set and PH2 dataset, and results are compared with State of Art models U-Net and SegNet.

Keywords: Skin Lesion Segmentation,Convolutional Neural Network(CNN), Dermoscopic Images,Convolutional Deconvolutional Neural Networks(CDNN).

1 Introduction

The outer region of the body is known as the skin, which is the largest organ. The total area is 20 square feet. It helps in regulating the body temperature and provides sensations like touch, cold, and heat. It is exposed more to the surrounding environment and may get in touch with pollution, dust, and radiation. These are the reasons for skin diseases and affect the functionality of the body. The skin has three layers. Dermis (Inner Layer), which is having Connective tissue, hair follicles. Epidermis (Outer Layer), which provides a waterproof barrier and forms skin tone. Deeper layer (Hypodermis), which has fat and connective tissue. The outer layer epidermis, which is composed of three types of cells. (1) SQUAMOUS: These are residing on the surface. The shape of these cells is flat and scaly. (2) BASAL: These are round cells. (3) MELANOCYTES: These cells provide color and save from skin damage identified at an early stage. It can spread deeper into the body and will affect other parts of the body. Firstly, the diagnosis of melanoma segmentation of a lesion followed by the extraction of features and then classification. Samples of images of skin lesion images are shown below in Fig.1

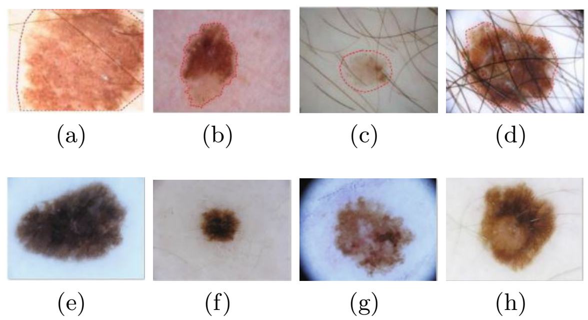


Fig. 1. Sample Dermoscopic images for Lesiion segmentation. (a) with large sizes; (b) with irregular borders; (c) low contrast with surrounding part; (d) artifacts and few other sample images of ISIC 2017 data set.

Nowadays, Medical Image Processing is one of the fast upcoming research fields. Getting results with more accuracy is more desirable in any research field. Segmentation with more accurate results plays a vital role in disease diagnosis, disease monitoring, and further treatment and planning. Segmentation [26] of an image by humans is laborious, tedious, and time-consuming. Segmentation by automated algorithms for segmentation with more accuracy is preferable. There are few factors for measuring the performance of a segmentation method. They are Region of Interest, Behavior of a segmentation algorithm, Performance of technique in terms of previous results. There are many advantages and disadvantages to each segmentation technique. There are benchmark measurements to evaluate the results.

Segmentation plays a vital role in Registration, image labeling, and tracking the motion. For example, in the heart-related segmentation, segmentation [7] of left ventricular (LV) in cardiac images. To find out the output of the heart and volume ratio of ventricular, segmentation of left ventricular is mandatory, and in the same way to get the information about the thickness of the wall it requires analysis of wall motion which in turn requires details of segmentation of left ventricular[11]. Implementation of required segmentation methods requires a good knowledge of the data and underlying problem. Validation and acceptance of segmentation techniques depend on simplicity in computations and supervision of the user. Semi-automatic and automatic segmentations are proposed and mostly used in the medical image segmentation process. Samples of original images and their Ground truths are given below in figure Fig.2.

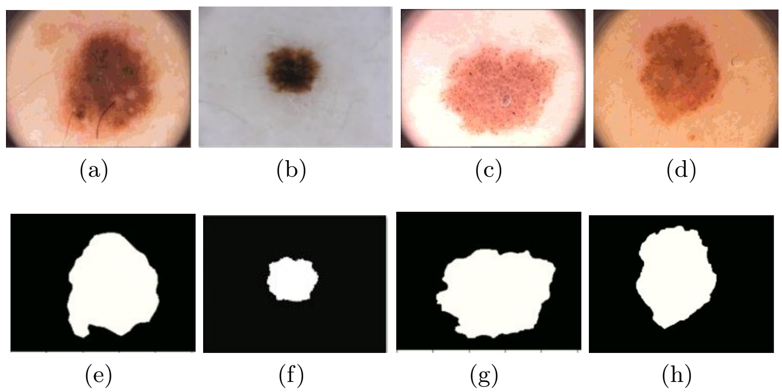


Fig. 2. Original images (a),(b),(c),(d) and Ground Truths(e),(f),(g),(h) from PH2 data set((a)(b)(e)(f)) and ISIC 2017((c),(d),(g),(h))data set.

Validation and acceptance of segmentation techniques depend on simplicity in computations and supervision of the user. Semi-automatic and automatic segmentations are proposed and mostly used in the medical image segmentation process. Manual segmentation of an object involves manually drawing the borders by experts. Usually, manual segmentation takes more time so, it is tedious and time taking. It depends on experts like more number of experts do the work differently at a time (Inter-rater)[18,25] or the same expert does the same in different ways in different time of intervals (Intra-rater), and it will not be a reproducible[25]. Manual segmentation provides ground truth for fully automatic and semi-automatic segmentation techniques. It is still mostly used in clinical diagnosis if there is no time constraint [2,6].In the Semi-automatic segmentation method, less human interactions will be there for the initialization process and correcting results [3]. This method combines human services and computer services. These semi-automatic segmentation methods depend on intra and inter rate reliability. In the case of the fully automatic segmentation[4], work will be performed without human involvement. Mostly model-based methods are involved besides soft computing methods. In these techniques, automatic information like image size, image color, brightness, etc. is required to have robust algorithms. Developing the automatic segmentation algorithm to get high accuracy[23] is a challenge because the human mind is having special knowledge with high visual processing. Nowadays, automatic segmentation methods are not accepted in clinical diagnosis but they are advantageous in processing.
Artificial Neural network is one of the supervised clustering methods, which

involves mathematical operations to be applied to the inputs (Features) and results are obtained at output nodes. Parameter values should be computed while training Artificial Neural Networks in such a way that prediction error is minimized.
3D image segmentation[13] is a difficult and challenging task and it can be handled by model-based segmentation techniques. Deformable methods are used to segment anatomic structural mages by building a model that takes priority information like size, location, orientation, and shape. The main property of deformable methods is the capability of adjusting with a change in biological structures over time and among the different individuals [10].

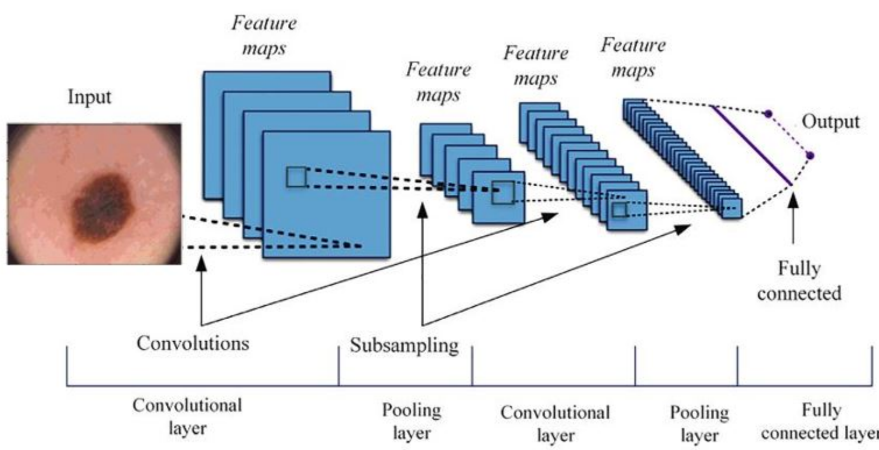


Fig. 3. Basic Structure of CNN

Artificial Neural Network[21] includes a non-parametric method, so no parametric distribution is considered for the data. Modeling of nonlinear dependencies in the given data is done using hidden layers of ANN. The training process in ANN is very complex, still, the ability of modeling non-trivial distributions includes practical advantages.

The other sections of the paper are arranged as follows: Section 2 represents a survey on research. The proposed method has been described in Section 3. Implementation, Results have been presented in Section 4, Section 5 and Concludes in Section 6 along with the highlighting the directions for future research.

2 Literature Survey

Medical Image Segmentation is an active topic of research with more challenging datasets. Traditionally, skin lesion segmentation methods mainly include clustering region-based method, and model-based methods [2,3,6].

In general, the first step in the image segmentation process is threshold-based segmentation because it is not useful to segment all images desirably [14]. As a solution for this drawback, the threshold technique based on the gradient for the segmentation[20] was proposed. In this method, first of all, parameters will be estimated with the help of the iterative process. The further process will be carried out by using these estimated parameters and the obtained results are more accurate compare to previously used threshold methods.

Labeling is an important task because experts should do it and it will take more time. Hence, it is not good to use supervised segmentation for a large amount of data. A better solution for the same issue is the usage of a semi-supervised segmentation method, which provides an alternative solution from a cost point of view. Semi-supervised segmentation methods give good results in terms of accuracy values compared to unsupervised segmentation techniques [13]. Clustering will be done using unsupervised segmentation based on unlabeled training data to find the decision boundaries [17,9,15].

Threshold-based segmentation will consider only intensity values, no other information like location. So, special information is not considered in the threshold-based segmentation. Hence, Because of this, there may be a chance to suffer from problems like noise sensitivity and inhomogeneity in intensity values of the image. These problems lead to an increase in complexity in segmentation and false results [1,24].

Region growing method leaks the tissues if there is no proper information about boundaries and if contrast is low. This method works fine with homogeneous regions. The drawback of the region-based method is noise sensitivity and it results in disconnected regions due to the noise. This method is useful in radiology applications like bone, lung, and tumor segmentation and is used in extracting lesions.[12].

The fuzzy C-means method is used for the segmentation of different body parts [22]. Due to iterative nature, the Fuzzy C-means method will take more time to process and to solve this problem Bias corrected Fuzzy C-means (BCFCM) clustering method is proposed. BCFCM is used to segment brain images and provides results with good quality, in this way it is very much useful for brain tumor segmentation [5].MRF is one of the unsupervised clustering methods, which is used to integrate information in the clustering techniques and it reduces the effect of problems like clusters overlapping and noise effect[8]. It can handle complex data dependencies and results in high accuracy in segmentation [16]. The segmentation of the cone-beam CT images of the tumor can be done by hidden MRFs.

3 Proposed Technique

3.1 Proposed lesion segmentation algorithm

The structure of CDNN of the proposed model is developed from the basic architecture of the Convolutional neural network (CNN) by modifying the classification part with the segmentation part. It means that a fully Convolutional network[19] is replaced with Deconvolutional networks to provide symmetric up sampling architecture.

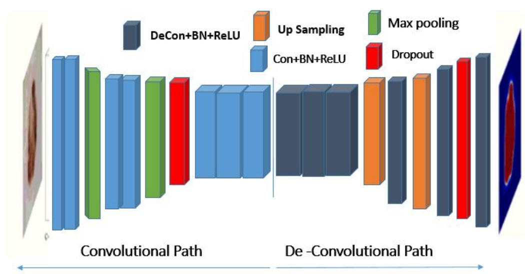


Fig. 4. Schematic diagram of the proposed Architecture

The proposed algorithm which is presented below is successful for the problem of skin lesion segmentation with data sets PH2 and ISIC 2017 and it relies on the convolutional part (Convolutional layers with different kernel sizes (5x5, 4x4,3x3, Batch normalization, ReLU activation function and dropout layer (0.5) as well) and Deconvolutional part(Deconvolutional layers with kernel size 3x3, Batch normalization, ReLU activation function, dropout layer (0.5) and Upsampling as well) and the performance metrics IOU, Accuracy, and Loss functions. The complete diagrammatic representation of the proposed method is shown in figure Fig.5.

The algorithm applied in steps as follows:

- 1. Resize the images and convert label images to indexed images.
- 2. Hyper parameters tuning
- 3. Tune the hyper parameters of the networks.
- 4. Pre-processing: Augmentation(Rotation, Flipping)
- 5. Performing Train, Test, and Validation based on splitting the data.
- 6. Apply the metrics IOU, Accuracy, and Loss Function.
- 7. Examine the performance.

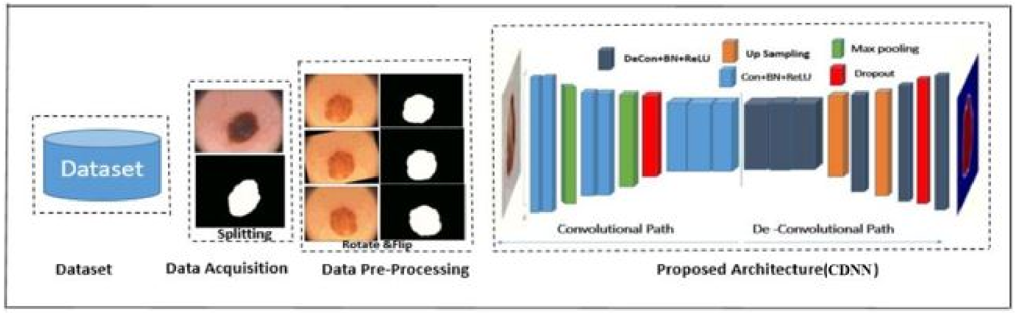


Fig. 5. Schematic diagram of the proposed methodology

4 Implementation

As it is mentioned in previous sections. The Proposed Architecture of Convolutional and Deconvolutional neural network is developed from basic architecture of CNN as shown in figure Fig.3., by modifying fully convolutional networks to Deconvolutional networks. While training the proposed model, stochastic gradient descent (SGD) is adopted with batch size 18, learning rate 0.001, decay 0.0005 and momentum 0.9 along with Adam optimization. Maximum number of epochs is 100. In order to improve the performance, augmentation technique is adopted which includes flipping and rotation.

4.1 Experimental Setup

Model training has been performed on Nvidia Quadro P5000 GPU with a 10.2 CUDA version and Driver Version 440.100, 16GB RAM CPU machine with a 64-bit Ubuntu Linux OS machine. The PH2 data set is having 200 images and 25% of these are given for testing.ISIC 2017 data set is having 2000 images, 500 images are given for testing.

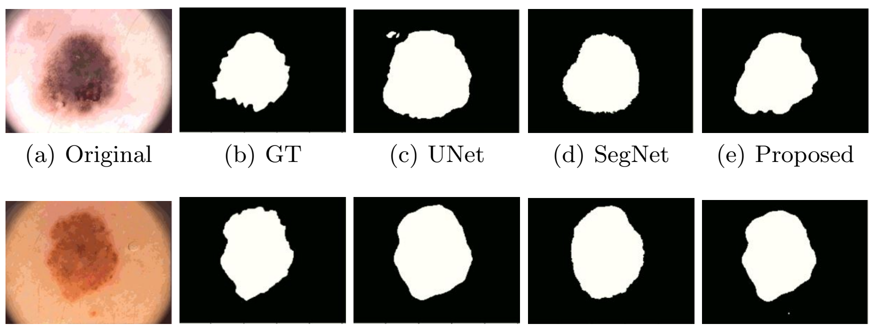
4.2 Evaluation Metrics

Quality of emotion labeling is generally subjective. It is challenging to correlate any evaluation metric with human judgement quality. A possible way to mitigate this challenge is to use diverse evaluation metrics. With this aim, the following metrics have been considered to evaluate the translations.

- **Accuracy**:Accuracy can be defined as the mean value of all predictions and it is the ratio of the accurate value of predictions and total predictions.
- **Intersection over Union(IOU)**:it is also known as Jaccard index and measured as the ration of intersection and the union of true and predicted values.

- **Loss**:Cross-entropy loss is used as loss measurement and ranges from 0 to 1. Probability of prediction diverges if Loss is more else converges. Overall Loss and corresponding accuracy are shown in figure Fig.7. and results of proposed method are shown qualitatively and quatitatively in Table 1. and Fig.6.

5 Results & Evaluation



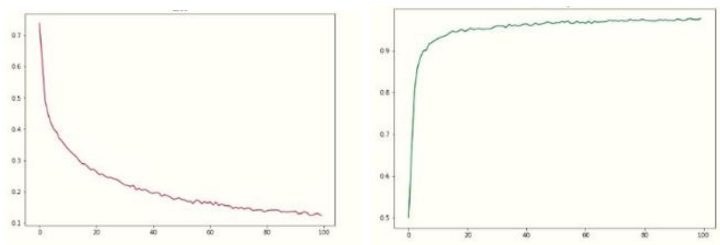
(a) Original (b) GT (c) UNet (d) SegNet (e) Proposed

(f) Original (g) GT (h) UNet (i) SegNet (j) Proposed

Fig. 6. Qualitative results of Proposed method from ISIC 2017(Top Row) and PH2(Bottom Row) Data sets.

Table 1. Quantitative Results of Proposed technique.

S.No	**Method**	**IOU**	**Accuracy**	**Loss**	**Data set**	**epochs**
1	UNet	46.88	77.46	53.12	ISIC 2017	100
	Proposed	**47.42**	**80.56**	**52.58**		
2	SegNet	90.10	91.57	27.00	PH2	100
	Proposed	**90.94**	**92.66**	**9.06**		



(a) Overall Loss (b) Overall Accuracy

Fig. 7. Graphical representation of over all loss and accuracy values.

6 Conclusion

The Literature survey and experiment and results, presented in this paper regarding the segmentation of skin lesion with the help of Dermoscopic images, will have a good impact on medical applications like diagnosis and further treatment with more accuracy. The development of a good segmentation technique is always necessary to find out the segments with the help of labeled data while using supervised techniques for segmentation. The famous data sets ISIC 2017 lesion segmentation challenge data set and PH2 data set are used in order to train, test, and examine the performance of the proposed method and to compare the performance with different techniques. The results,which are obtained in this model,shows the superiority of the proposed technique with accuracy 92.66% with PH2 data set, 80.56% with the ISIC 2017 data set, IOU is 90.94% with PH2 data set, 47.42% with the ISIC 2017 data set, and also in case of Loss, the proposed method is showing promising results shown above, Table 1. The case study presented in this paper shows few suggestions like the increase in data set size and change in preprocessing methods and architecture can improve the overall performance. Future work can be carried out on new data sets by including failed cases with the help of optimized algorithms for more medical applications.

References

1. Anand, P., Bharanitharan, K., Wu, J.: Algorithm and architecture for adaptive motion estimation in video processing. IETE Technical Review **30**(1), 24–30 (2013)
2. Bae, K., Shim, H., Tao, C., Chang, S., Wang, J., Boudreau, R., Kwoh, C.K.: Intra-and inter-observer reproducibility of volume measurement of knee cartilage segmented from the oai mr image set using a novel semi-automated segmentation method. Osteoarthritis and cartilage **17**(12), 1589–1597 (2009)
3. Bankman, I.: Handbook of medical image processing and analysis. Elsevier (2008)
4. Bezdek, J.C., Hall, L., Clarke, L.: Review of mr image segmentation techniques using pattern recognition. Medical physics **20**(4), 1033–1048 (1993)

5. Dheeba, J., Singh, N.A., Selvi, S.T.: Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach. Journal of biomedical informatics **49**, 45–52 (2014)
6. Gaonkar, B., Macyszyn, L., Bilello, M., Sadaghiani, M.S., Akbari, H., Attiah, M.A., Ali, Z.S., Da, X., Zhan, Y., O'Rourke, D., et al.: Automated tumor volumetry using computer-aided image segmentation. Academic radiology **22**(5), 653–661 (2015)
7. Gonzalez, R.C., Woods, R.E., Eddins, S.L.: Digital image processing using MATLAB. Pearson Education India (2004)
8. Hassanien, A.E., Moftah, H.M., Azar, A.T., Shoman, M.: Mri breast cancer diagnosis hybrid approach using adaptive ant-based segmentation and multilayer perceptron neural networks classifier. Applied Soft Computing **14**, 62–71 (2014)
9. Lee, C., Unser, M.A., Ketter, T.A.: Automated connectivity-based thresholding segmentation of midsagittal brain mr images. In: Visual Communications and Image Processing'96. vol. 2727, pp. 713–724. International Society for Optics and Photonics (1996)
10. Malladi, R., Sethian, J.A., Vemuri, B.C.: Shape modeling with front propagation: A level set approach. IEEE transactions on pattern analysis and machine intelligence **17**(2), 158–175 (1995)
11. McInerney, T., Terzopoulos, D.: Deformable models in medical image analysis: a survey. Medical image analysis **1**(2), 91–108 (1996)
12. Moores, M., Hargrave, C., Harden, F., Mengersen, K.: Segmentation of cone-beam ct using a hidden markov random field with informative priors. In: Journal of Physics: Conference Series. vol. 489, p. 012076. IOP Publishing (2014)
13. Ni, T., Xie, L., Zheng, H., Fishman, E.K., Yuille, A.L.: Elastic boundary projection for 3d medical image segmentation. In: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 2104–2113 (2019)
14. Oliver, A., Freixenet, J., Marti, J., Perez, E., Pont, J., Denton, E.R., Zwiggelaar, R.: A review of automatic mass detection and segmentation in mammographic images. Medical image analysis **14**(2), 87–110 (2010)
15. Ostu, N.: A threshold selection method from gray level histogram. IEEE Trans, on System **9**, l (1979)
16. Parmar, H., Talati, B.: Brain tumor segmentation using clustering approach. In: 2019 Innovations in Power and Advanced Computing Technologies (i-PACT). vol. 1, pp. 1–6. IEEE (2019)
17. Pham, D.L., Xu, C., Prince, J.L.: Current methods in medical image segmentation. Annual review of biomedical engineering **2**(1), 315–337 (2000)
18. Ramkumar, A., Dolz, J., Kirisli, H.A., Adebahr, S., Schimek-Jasch, T., Nestle, U., Massoptier, L., Varga, E., Stappers, P.J., Niessen, W.J., et al.: User interaction in semi-automatic segmentation of organs at risk: a case study in radiotherapy. Journal of digital imaging **29**(2), 264–277 (2016)
19. Rohlfing, T., Maurer, C.R.: Multi-classifier framework for atlas-based image segmentation. In: Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004. vol. 1, pp. I–I (2004)
20. Sajadi, A.S., Sabzpoushan, S.H.: A new seeded region growing technique for retinal blood vessels extraction. Journal of medical signals and sensors **4**(3), 223 (2014)
21. Saxena, N., N., K.B., Raman, B.: Semantic segmentation of multispectral images using res-seg-net model. In: 2020 IEEE 14th International Conference on Semantic Computing (ICSC). pp. 154–157 (2020)
22. Schmidt, M.: Automatic brain tumor segmentation (2005)

23. Sharma, N., Aggarwal, L.M.: Automated medical image segmentation techniques. Journal of medical physics/Association of Medical Physicists of India **35**(1), 3 (2010)
24. Sun, K.: Development of segmentation methods for vascular angiogram. IETE Technical Review **28**(5), 392–399 (2011)
25. White, D.R., Houston, A.S., Sampson, W.F., Wilkins, G.P.: Intra-and interoperator variations in region-of-interest drawing and their effect on the measurement of glomerular filtration rates. Clinical nuclear medicine **24**(3), 177–181 (1999)
26. Zhou, Y., He, X., Huang, L., Liu, L., Zhu, F., Cui, S., Shao, L.: Collaborative learning of semi-supervised segmentation and classification for medical images. In: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 2074–2083 (2019)