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Skin Lesion Segmentation Using Deep Learning Methods

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ABSTRACT

Automatic detection and extraction of lesion regions from dermoscopy images is a primary and essential step in the process of diagnosing the skin lesions. Early detection of these lesions may reduce the intensity of the problem and improve the survival rate by 14%. This is a challenging task due to high variations in the appearance of the regions, orientation and the size of lesion regions. In this paper, the segmentation and classification are pipelined in a single structure which is implemented using deep learning methods. The network is trained and tested with standard dataset images and found that this method performs outstandingly than earlier feature or contour based algorithms.

Keywords: *skin lesion segmentation, melanoma, deep network, fully connected convolutional neural network*

INTRODUCTION

The study on dermoscopic images has been proven to be one of the useful way of reducing the number pre-assumptive diagnosis that are ought to be confirmed for histological skin biopsy [1]. These images are obtained by combining optical combination with cross polarized or liquid immersion integrating with low incidence of lighting. The use of dermoscopy is crucial for estimating the border structural information of the lesion region and also provides some clinical information like asymmetry, irregularity of that particular region. It is observed that many of the dermatologists consider the history of the same skin lesion which can be useful in diagnosing the evolution time of the region.

Melanoma is observed to be one of the most aggressive lethal tumors and observed that around 80% of the skin cancer deaths are due to this type of tumors. One of the most effective ways of diagnosing this tumor is dermoscopy; which is non- invasive and cost effective. This type of imaging is very useful in determining whether the region is lesion or not [2].

Automatic lesion region extraction from dermoscopic images is not trivial due to variations in the appearances of the region in terms shape, color and size of the affected region. It can be observed that in some of the images the edges are blurred, irregular, low contrast etc; these effects may further increase the complexity of the challenge of segmenting the lesion regions. To address the above mentioned limitation deep learning techniques are been introduced.

This paper presents an effective approach of extracting the lesion region using deep learning techniques, since deep learning techniques shows ultimate performance in classification and segmentation of region in the image and presented customized fully convolutional neural network is designed to segment the lesion region. Results shows that automatic detection of skin lesion region through deep analysis is far better than traditional feature based machine learning algorithms. The paper is organized as follows

RELATED WORK

In recent times computer aided automatic diagnosis methods have been proposed to help and accelerate the diagnosis process. These methods are broadly classified into two categories

- Computer Vision and machine learning methods
- Deep learning methods

The first categorical methods focuses on low level features like color, edges texture and others [3].In these methods, different features simplifies the task of a machine such that it can use these features for further predictions. A methodological approach to the classification of pigmented skin lesions in dermoscopy images is presented in [4]. In this approach at first, automatic border detection is performed to separate the lesion from the background skin. Shape features are then extracted from this border. For the extraction of color and texture related features, the image is divided into various clinically significant regions using the Euclidean distance transform.

Approaches based on the classification of histopathological images from skin cancer biopsies samples are proposed in [5] and [6]. A semi-advised learning model combines the benefits of deep belief networks and SVM with a self-advising capability to deal with the problem of an erroneous classification operation due to insufficient number of labeled data, which is a common situation due to the difficulties in obtaining labeled data from experts.

An unsupervised method for early melanoma detection called ASML is presented in [7]. The method combines the contour extraction together with the Delaunay triangulation for obtaining a binary mask of the lesion. The method is very effective when dealing with benign lesions, while its performance decreases when melanoma images are processed. Then, a set of features related to the colors and the geometry properties of the masks are used for classifying the dermoscopic images.

A deep learning based approach, namely the fully convolutional neural network (FCN), has been proposed to automatically identify lesion borders, based on the combination of images form less or more challenging skin lesions [8], [9]. FCN is a neural network architecture that performs object detection by combining low-level appearance information with high-level semantic information. Such a method, originally proposed to deal with the segmentation task only, has been further developed as a fully convolutional residual net (FCRN) approach, which addresses simultaneously the segmentation and the classification task.

Majority of the segmentation algorithm that was employed to extract the lesion region includes fully connected convolutional neural network (FCNN) but some of these networks has issues with boundary precision in image segmentation and ensemble learning. For the application of classification it requires both significant amounts of time and computing resources. There is a need for a more elegant method requiring less computing resources and data are required, this is the scope for new research algorithm in the field of lesion segmentation.

PROPOSED METHODOLOGY

The generalized block diagram of the proposed methodology is presented in below figure 1. This method contains two phases training and testing

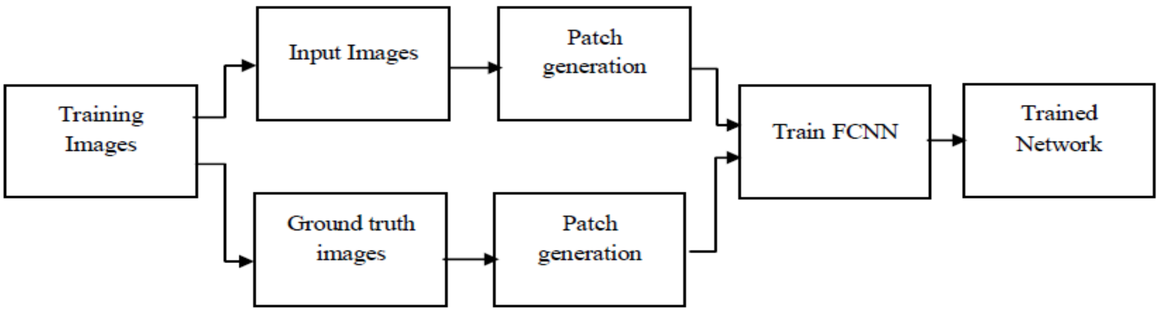


Figure1. *Generalized block diagram of network training for proposed methodology*

In this phase, the training samples and their ground truth images are partitioned into non overlapped blocks of size *mxn* and these patches are directed for training the fully connected convolutional neural network (FCNN).

Convolutional Neural Network

The purpose of the convolutional layer is to extract features from the input data. It learns image features using small squares of input image and creates a feature map by maintaining spatial relation between pixels. After giving input to the convolutional layer, convolution is performed between input and the features learned by the network. Convolution is a linear process which is element wise matrix multiplication and addition. And output convolutional layer has same resolution as input. Each convolutional layer output (Feature map) is passed through ReLU layer. ReLU is a Non-linear operation used to normalize the output of convolutional layer. It is applied per pixel and replaces all negative pixel values in the feature map by Zero. Output feature map of ReLU layer also have same resolution as input image.

Pooling reduces the dimensionality of each feature map but retains the most wanted information. In our architecture we use Max pooling in which the largest pixel value from the rectified feature map within the selected window is taken. Here we stack all the output feature maps of pooling layer and give as input to fully connected layers. The output of the final pooling layer acts as an input to the fully connected layer. Conventionally Fully connected layer resembles a multi-layer perceptron. Fully connected layer uses Soft Max as the final classification layer to predict the given input category [10] [11].

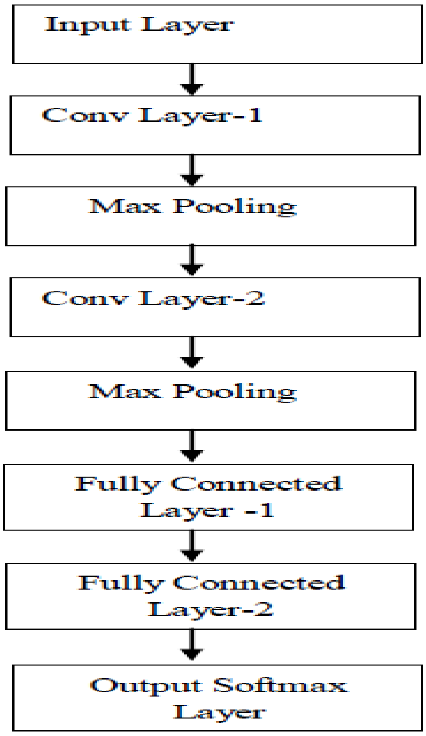


Figure2. *A typical example Convolutional neural network architecture*

In this work, the skin image patches with its respective ground truth patch are subjected for training the network. Here to speed up the process, VGG16 network is used to create segmentation layers with "segnet" functionality in Matlab.

Experimental Results

The images that were used in this were taken from [12] for which the ground truth images were also provided to evaluate the performance of the segmentation algorithms. The images are downscaled with a factor of '3', so that the processing may be done at faster rate. The entire approach is trained and tested on CPU with parallel computing process with Matlab 2018a version. The network designed for the present application is depicted below which contain five stage convolutional network. The present method is compared against the method mention in [13], which is feature based method as we try to show that the deep networks provide more accurate results than ML methods.

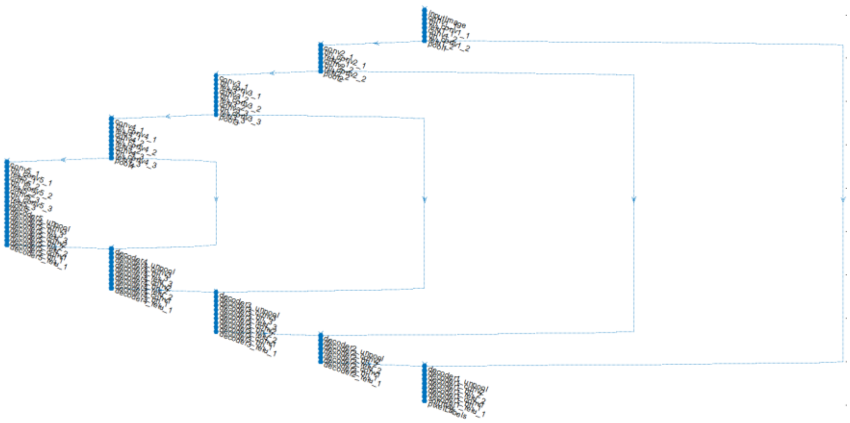


Figure3. *CNN designed for the proposed approach*

METRICS FOR EVALUATION

In order to quantify and validate the performance of the proposed approach certain metrics are employed where the segmented image is been compared against the manual ground truth segmented image from dataset.

Table1. *Comparison of manual segmented and automatic segmented*

	Region Present	Regional Absent
Region Detected	True Positive (TP)	False Positive (FP)
Region not detected	False Negative (FN)	True Negative (TN)

Sensitivity: $Se = \frac{TP}{TP+FN}$

Specificity: $Sp = \frac{TN}{TN+FP}$

Positive Predicted Value: $PPV = \frac{TP}{TP+FP}$

Negative predicted Value: $NPV = \frac{TN}{TN+FN}$

Accuracy: $Acc = \frac{TP+TN}{TP+FP+FN+TN}$

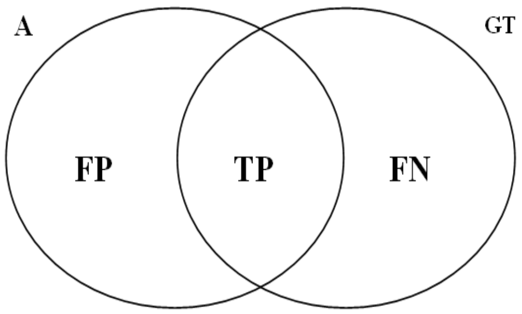
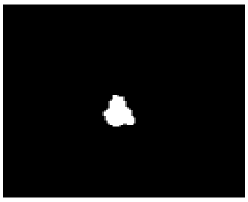
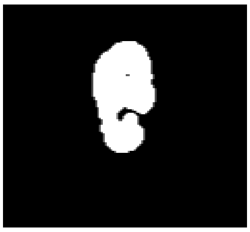
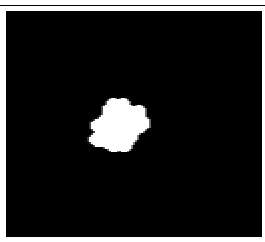


Figure4. *Venn diagram representation and intersection of segmented region where GT: ground Truth Image, A: Automatic segmented Image*

Se, Sp, represent the well classified vessels and non vessels, PPV is the ratio of the pixels that are correctly classified, NPC is the ratio of the pixels of the background that are correctly classified as background; ACC is the global ratio of total correctly classified pixels [14].

To perform the experiments, the image dataset is partitioned into training and testing sets, each image is scaled into square matrix and blocks partitioned into 16x16 blocks and in our experiments a total of 3200 number of patches were used for training the network. The convolutional network designed for segmentation using segnet with Vgg16 network.

Table2. *Segmentation outputs of the proposed approach and its ground truth images*

S.NO	Input Image	Proposed approach	Vimal et.al [13]	Ground truth
1				
2				
3				

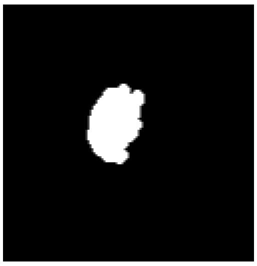
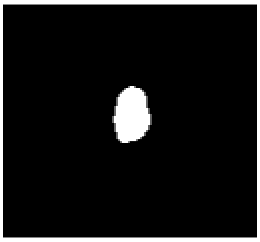
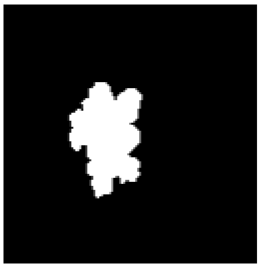
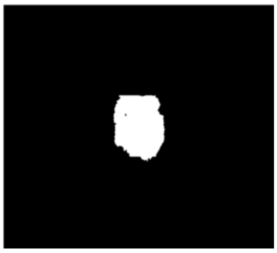
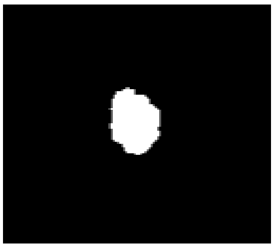
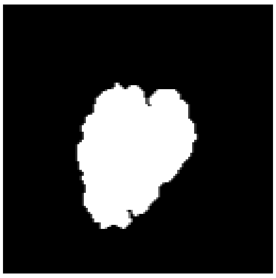
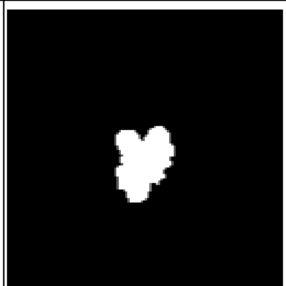
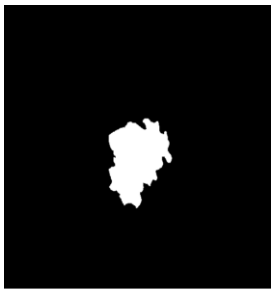
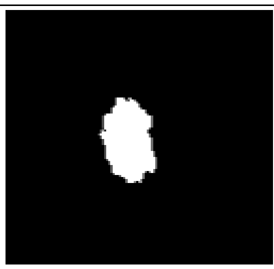
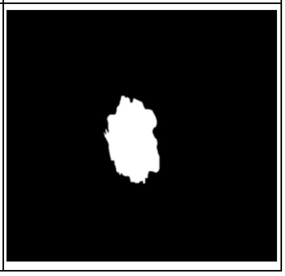
4				
5				
6				
7				
8				
9				
10				

Table3. *Performance evaluation of the proposed approach in terms of metrics*

Input Image S.NO	SE	SP	PPV	NPV	ACC
1	0.994	0.998	0.904	0.999	0.998
2	1	0.992	0.926	1	0.993
3	0.9110	0.997	0.943	0.996	0.994
4	0.999	0.995	0.939	1	0.995
5	0.986	0.988	0.621	0.99	0.988
6	0.784	0.99	0.987	0.962	0.964
7	0.953	0.999	0.980	0.998	0.997
8	0.974	0.992	0.964	0.991	0.987
9	0.920	0.999	0.984	0.991	0.990
10	0.909	0.997	0.948	0.995	0.993
AVG	**0.943**	**0.994**	**0.916**	**0.992**	**0.989**

Table4. *Performance analysis of the approach presented in [13]*

Input Image S.NO	SE	SP	PPV	NPV	ACC
1	0.958	0.989	0.98	0.99	0.99
2	0.941	0.982	0.824	0.995	0.979
3	0.937	0.995	0.899	0.99	0.99
4	0.725	0.99	0.874	0.972	0.967
5	0.978	0.991	0.7002	0.99	0.991
6	0.775	0.868	0.518	0.969	0.858
7	0.929	0.993	0.855	0.996	0.990
8	0.927	0.985	0.935	0..984	0.975
9	0.875	0.994	0.892	0.993	0.988
10	0.993	0.971	0.842	0.99	0.972
AVG	0.903	0.975	0.831	0.987	0.97

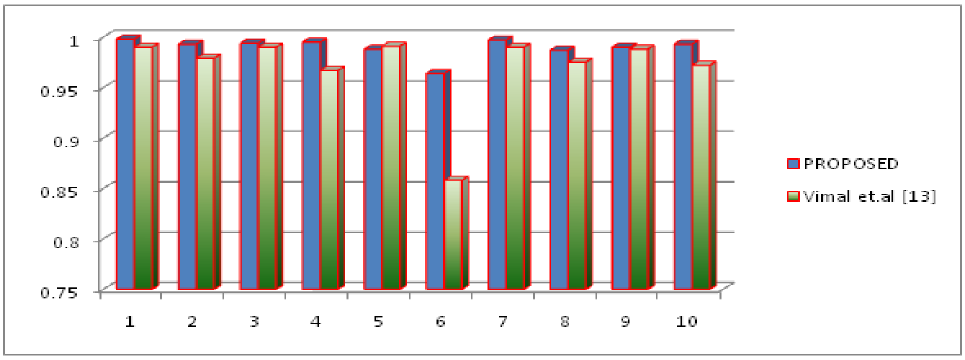


Figure5. *Accuracy of proposed and existing method presented by Vimal [13]*

From the analysis and experimental results, it was observed that deep learning method proposed in this work could attain an average accuracy of 98.9% which is far better than conventional machine learning method with thresholding proposed in [13]. In the traditional, the assumption of constant values is cumbersome and the efficiency of the algorithm is relied on the selection of the parameters, hence this limitation was overcome with the current work, moreover the border deficiency problem with earlier deep learning is also treated in this current work.

CONCLUSIONS

A fully connected convolutional neural network for lesion region segmentation for skin dermoscopic images is proposed in this paper. The network designed is based on transfer learning where Vgg16 network is used for segmenting and classifying the abnormal and normal region. The performance of the method is evaluated using several metrics and compared against with respect to ground truth and traditional feature based machine learning method. It was observed that this method could attain superior results meeting the objectives of the work in segmenting efficiently the lesion regions.

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