Automatic Recognition of Skin Cancer using Fully Convolution Networks and Conditional Random Fields

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Abstract*: *Skin cancer is one of the deadliest diseases that have been increasing all over the world. Automatic identification of lesion from low contrast dermoscopic images, over-segmentation of images and under-segmentation of images is a challenging task in the medical field. In order to overcome these challenges, we have proposed a Computerized Diagnosis system with deep fully convolution network (10*1 layer network) for segmenting the skin lesion which has been trained on end to end with 50% of dataset. Furthermore, Conditional Radom Field has been integrated with the existing framework for enhancing the segmentation performance and we added ensemble classifier technique called Bagging for accurate classification of lesion images into various categories. The proposed architecture is extensively evaluated on PH^2 dataset. Experimental results showed that proposed method out performs well in comparison with the existing method. These results prove that the proposed system is more effective and suitable for any kind of medical images.

Index Terms*: *Bagging, CAD, Conditional Random Field, Dermoscopy

I. INTRODUCTION

Malignant lesion is the leading cancer in all over the world. United States of America is the leading country in skin cancer. According to skincancer.org, the United States of America have the following statistics: 192,310 people were affected by melanoma. Among these 95,830 were affected at the top layer of the skin called Epidermis and the remaining people were affected at the second layer of the skin called Dermis. Out of these people, nearly 7,230 people were died in each year. Survival rate of the patients can be increased only when the lesion is identified at the earlier stage.

Charles et al [3] classified the melanoma based upon their thickness and ulceration into four different stages from T1-T4. In each stage the survival rate of the patient gets decreasing. The types of melanoma has been described in **Ta**

Melanoma can be diagnosed at the early stage using different techniques. Initially, Radiation therapy and immunotherapy has been used to increase the survival rate of the patients. Christopher et al [4] stated that integration of radiation and immunotherapy cures skin cancer at the higher level. But this integration provides side effects to people. Hence this system is not used further.

Melanoma Stage	Found in body	Tumor size	Survival Rate
Superficial Spreading Melanoma (T1)	Arms, Legs, Chest	Less than or equal to 1mm	10-years
Nodular Melanoma (T2)	Chest, head, neck	1.01mm-2.00mm	10-years
Lentigo Maligna Melanoma (T3)	Face and neck	2.01mm-4.00mm	5-years
Acral Lentiginious Melanoma (T4)	Palms, hands and feet	Greater than 4.00 mm	1-year

Dermoscopy tool was developed to improve the performance of the detection of melanoma. It is a non imaging tool which is used to identify the small spots on the skin with high clarity. Most of the dermatologists were disappointed while performing inspection over this tool. Dermoscopy tool provides more erroneous results compared with the normal human eye interpretation.

Automated identification of lesions from dermoscopy images involves a variety of difficult tasks. The difficulties includes similarity between lesion and non-lesion, presence of hairs, sweat bubbles around the lesion may decrease the clarity of the lesion and provides some wrong results.

The flow of the paper is organized as follows: Section-II discusses the literature survey for this analysis of medical images; Section-III discusses about Proposed Architecture; Section-IV compares proposed results with existing system and conclusions were stated in Section-V.

II. RELATED WORK

Several researchers have developed different types of techniques for detecting the melanoma at the earlier stages.

Computer Aided Diagnosis system [12] has been used to identify the skin lesion at the earlier stages. It takes the dermoscopic images as an input and classifies the lesion using machine learning and deep learning techniques. This system mainly involves four different steps namely I) Pre-Processing, II) Segmentation, III) Feature-extraction and IV) Classification.

Initially Non-Dermoscopic images were analyzed first by taking

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the lesion images with normal cameras. These images are called as macroscopic images. Pixel wise regions were merged in this method and a likelihood function is applied to extract the skin lesions based on regions.

In Boundary detection techniques [2], [15], [5], Principal Component Analysis (PCA) was used to cluster the lesion and non-lesion and detect the boundaries of the lesion using down-sampling technique and classifies the melanocytic lesion. Fixed Grid Wavelet Network (FGWN) which is a 3-layer network that segments the input image based on a wavelet lattice. 441 features were extracted from this segmented lesion. This method acquires higher accuracy in pre-processing technique rather than classification of the results.

Recently Machine Learning techniques have been integrated into the medical field for automatic detection of melanoma. [1], [9] Convolution and Deconvolution neural networks were used to enhance the segmentation performances. Deeper network architecture has been built to process the input and the features have been extracted. Ivan et al [8] represents a model called DermaKNet that incorporates the knowledge of skin experts to Convolution Neural Network architecture (CNN). It is a CAD system that extracts the features of dermatologist experts which may lead to provide accurate results and a higher satisfaction of all the dermatologists. CNN was lacked in enhancing the segmentation methods.

Deep Learning techniques were used for improving the performance of the network architecture which provides exact results. [13]. Deep Residual Networks were used to classify and segment the images using Fully Connected network architecture with Residual Network (FCRN). It is 7*7 network pool layer that extracts the global features from the image which includes all the smaller features presented across all the surroundings of the image. ABCD features [11] which represent the Asymmetry, Border, Color, Diameter and Evolution of the skin lesion were the major features of the lesion. Total Dermoscopy Score (TDS) has been calculated using these features. Soft Max, SVM and ensemble [10], [7] classifier has been used for classifying the lesions.

III. PROPOSED METHOD

The main objective of this proposed system is to detect the melanoma at the earlier stage even if the acquired image quality is poor. The proposed method undergoes four different stages of operations namely: Pre-Processing, Segmentation, Feature Extraction and Classification.

A. General Description of the System

The main pipeline of the proposed method is depicted in **Figure-I.** It comprises the following steps:

1) A dermoscopic image is first passed into Dull Razor technique to remove the hairs and sweat bubbles.
2) Pre-Processed image is then sent into the Convolution Architecture to study the features of the lesion
3) Conditional Random Field is then applied to the trained image to segment the skin lesion
4) ABCD Features were extracted from this segmented image
5) Bagging classifier has been used to classify the skin lesion based upon the above extracted features.

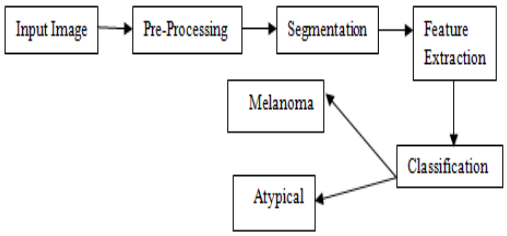
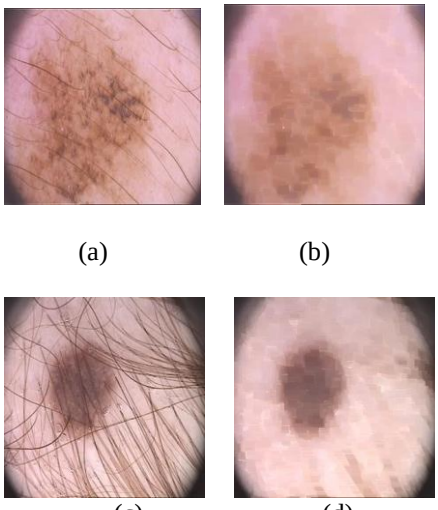


Figure-I: Pipeline of the Proposed System

B. Pre-Processing

Dull-Razor technique was used for Pre-Processing the skin image. It is an artifact removal technique that deals with different types of artifacts in images. Dermoscopy images were subject to different artifacts such as Hairs, sweat bubbles, presence of the blood vessels etc. Location and pixel of these artifacts were identified initially. Those identified pixels were replaced using Bilinear Interpolation technique and then the noise was removed using median filter. Pre-Processed image was shown in **Figure-II** (a,c) represents the original dermoscopic images taken using dermoscopy device whereas (b,d) represents the corresponding pre-processed image with respect to the original image. This technique enhances the visibility of the skin lesion accurately and suitable for any kind of imaging acquisition condition.



(a) (b)

(c) (d)

Figure-II : (a,c)Original dermoscopic image without pre-processing (b,d)Pre-Processed Image

C. CNN and CRF for lesion segmentation

In the previous work [14] Fully Connected Neural Network(FCN) model contains 19 layers with 290 and 129 parameters. This proposed model consist of FCN network with 10 layers with 290 and 129 parameters. The advantage of this proposed model is that to train a large amount of data with a smaller architecture.

A. Network Architecture

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The proposed CNN consists of 10 residual blocks. Each residual block consists of 1-1*1 Image Input Layer (I1), 2-1*1 convolution2dLayer (C1,C2), 2-1*1 ReluLayaer (R1,R2), 2-1*1 MaxPoolingLayer (M1,M2), 1 -1*1 Fully Connected Layer(FC), 1 1*1 Softmax Layer(S) and finally 1-1*1 Output Classification Layer (O). Architecture of the proposed method is described below in **Figure-III**

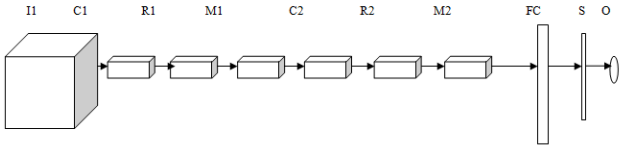


Figure-III: CNN Architecture

CNN integrate both local and global features and reduce the resolution in the output image. Lost resolution pixels were resampled using Upsampling and Downsampling layers. Upsampling layer is used for inverse process of pooling layer. It uses a activation function called Sigmoid activation function which increases the training performance. This model represents an mapping from a input image to segmentation map with the posterior probabiltiy values.

B. Conditional Random Field (CRF)

It is an probablistic undirected graph model [6]. CRF uses both local, global and spatial features which is very relevant to the segmentation of images.

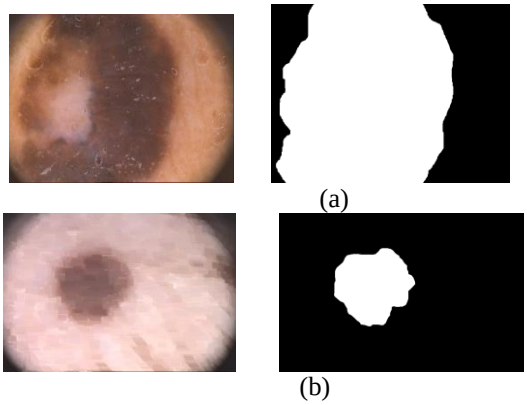
$$P\ (la|\ v_{(f,\lambda)}; \theta_\lambda\ ) = \frac{1}{Z(v_{(f,\lambda)})} \exp\ (-E\ (l, v_{(f,\lambda)}); \theta_\lambda) \quad \ldots(1)$$

Equation(1) represents the CRF expression where E (la, $v_{(f,\lambda)}$); θ_λ - energy function; v- Input voxel; la-label; f={x,y} along the spectral domain. Spatial information has been incorporated with the existing energy function to form a relationship with the voxel and the CRF graph.

$$E(la, v_{(f,\lambda)}; \theta_\lambda) = \Sigma_{\substack{p\epsilon M \\ \lambda\epsilon B}} \phi(la_p, v_p; \theta_\lambda) + \Sigma_{\substack{(p,q)\epsilon N \\ \lambda\epsilon B}} \psi(la_p, la_q, v_p, v_q; \theta_\lambda) \quad \ldots(2)$$

Equation (2) represents the updated energy function where M-total number of voxels ;N-total number of edges; ϕ-Unary Potential Function; ψ-Pairwise Potential Function. Feature Vectors were obtained from the feature map which was the output of the CNN training layer. Unary Potential energy has been calculated for each of the features present in the feature map. The main advantage of using this method is to adjust the threshold used in segmentation process based upon the energy function.

Inference algorithm is used to segment the regions. It is an iterative fashion which occurs multiple times to segment the regions. Initially, a soft-max activation function is run over an Unary Potential function across all the labels that were belongs to each nodes were initialized. Gaussian kernel were used to define the estimation of the prediction of the nodes. Combine the voxels that are belongs to a same category.Weight of the each label has to be taken. Finally, unary function has to be added to the initial CNN to get a new softmax activation function which results in the segmented regions. Segmented regions were depicted in **Figure-IV.** In Fig-IV (a) represents the segmented image of melanoma and (b) represents the segmented area for non-melanoma images.



(a)

(b)

Figure-IV: Segmented Image (a) Melanoma (b) Atypical

D. Feature Extraction

ABCD rule (Asymmetry, Border, Color, and Diameter) is a scoring technique that has been used to separate the melanoma from the normal skin lesions. The irregular variations should characterize all the differences occur within the lesion.

A. Asymmetry

Generally malignant lesion has irregular axes or shape compared with the benign lesion. Axes of the symmetry depend upon the axes of the centre of the gravity. Principal axes of symmetry states that

$$I(\varphi) = \Sigma_{(i,j)\epsilon L}\ Dist_\varphi^2\ (i, k) \quad (3)$$

$Dist_\varphi$ (i, k) is the distance between the current pixel and the horizontal line of the axes. The score of the asymmetry has been follows:

if (lesion is equal in both the axis)
Set asymmetric score as 0
else
Set asymmetric score as 2

B. Border

Normally a dermoscopic image is made up of eight equal octant planes. Border of the lesion has been estimated by using third order spline function on each of the slice of the sub-contour. The spline function is given by finding the Euclidean difference between the RGB color spaces (4) and (5).

$$\Delta E = \sqrt{(L1_{b1} - L1_{b2}{}^2) + (a1_{b1} - a1_{b2}{}^2) + (b1_{b1} - b1_{b2}{}^2)} \quad (4)$$

$$p(x) = p_1x^3 + p_2x^2 + p_3x^1 + p_4 \quad (5)$$

The score of the border is set as follows:

if (sub-contour is irregular)
Set score to 1
else
Set score varies from 2 to 8 based on the lesion

C. Color

Lesions have been appears in six different colors. Color is generally measured by using Euclidean distance between the pixels. A pixel color has been identified using threshold value. The distance of the pixel is lesser

than the threshold value then the skin lesion is present in that pixel. Suspicious color has been identified using the pixel count that belongs to that lesion color Melanoma has more than one suspicious color.

D. Different Structures of the System

Two different structures were predicted namely Pigmented networks and Geometrical properties. For each of the structure a score has been assigned from 0 to 5 and finally a dermoscopic score has been calculated using the equation (6).
Diff= result of two network model + classifier result (6)

Lesion is divided into 20*20 blocks to form a binary mask for finding the presence of pigmented networks on the lesion. If the RGB color spaces and threshold value is less than mask value then there is a presence of pigmented network otherwise pigment network is not available. Four lesion features were used to calculate the score of the geometrical properties called: fractal dimension, asymmetry index, circularity and elasticity. The score is set as follows:

```
if (elasticity > 0.85 & asymmetry index > 0.4)
    Set score=3
else if (elasticity < 0.85 & asymmetry index > 0.55)
    Set score=2
else
    Set score=0
```

E. Classification

In medical analysis, the dataset generally consists of both normal and abnormal cases in an improper ratio which results in a class imbalance problem. In order to overcome this imbalance problem deep learning classifier technique has been used. Ensemble classifier called Bagging technique has been used in this paper to classify the lesion from the extracted features. Features were divided into individual sub samples and then each of the samples is fed into a individual number of decision trees and a predictor is used to combine all those predicted results into a single output. Finally, the output is projected as a result of the classifier whether it is a lesion or not a lesion.

IV. RESULTS AND DISCUSSION

A. Dataset

PH^2 database is a publicly available dataset. This dataset is used in many of the skin classification algorithms. The main aim of developing this database is to identify the different type of lesions automatically using CAD system. The dataset contains 200 Images out of which 40 images were melanoma which include Lentiginious Melanoma also. And 80 images were atypical nevus images which include blue nevus and dysplastic nevus and the remaining 80 images were common nevus. All the dermoscopic images were taken using a vivo tool called dermoscopy and the images were stored in the format called .bmp which would be easier for systematic interpretation of melanoma diagnosis.

B. System Implementation

The Proposed architecture was implemented in MATLAB R2018b. In this method, the networks were trained with the Stochastic Gradient Decent Momentum (SGDM) optimization technique with the initial parameters. We set each of the parameters as (Maximum Number of Iterations: 5, Mini Batch Size: 4, Initial learning rate: 0.0001, and the Verbose Frequency: 1). Batch Normalization Layer and Rectified Linear Unit activation function has been added after the each of the Convolution 2d layer which makes the training progress faster even for the large amount of data.

C. Performance Metrics

Effectiveness of the proposed system has been evaluated using different metrics. Output of the segmentation and classification were assessed independently. This proposed method is compared with the ground truth of the clinical images. Evaluation metrics used for assessing the PH2 dataset includes Accuracy, Jaccard Index. The metrics are defined as follows:

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

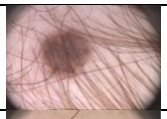
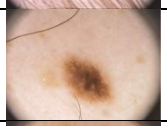
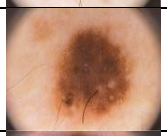
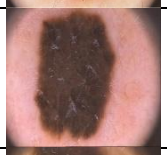
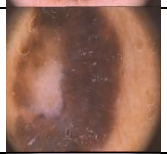
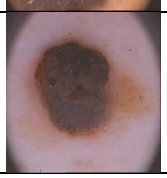
$$\text{Jaccard Distance} = \frac{TP}{TP+FN+FP}$$

TP, TN, FP and FN represent the number of true positives and negatives and the number of false positives and false negatives respectively.

D. Evaluating on PH^2 Dataset

Analyzing the effects of proposed method on PH^2 dataset based upon two different methods such as: Segmentation and Classification. These components included optimization techniques and ensemble method of classifier. Different Images from the dataset has been undergoes this proposed method for classifying the skin lesions. **Table-II** describes about the performance measure of each of the certain images in the dataset.

Table-II: Evaluation on PH^2 database

Image	Lesion Type	Accuracy	Jaccard Distance
	Common Nevus	0.8800	0.8571
	Common Nevus	0.8756	0.8452
	Atypical Nevus	0.8756	0.8573
	Dysplastic Nevus	0.8800	0.8467
	Melanoma	0.8800	0.8571
	Nodular Melanoma	0.8800	0.8496

Segmentation performance has been depicted in **Figure-V**. Segmentation performance has been compared with the basic deep convolution neural network and Combination of CNN and CRF. Average accuracy rate of the each method with different type of cancer were discussed. Each of the images was trained with the CNN network and then the segmentation has been done with the help of Conditional Random Field networks.

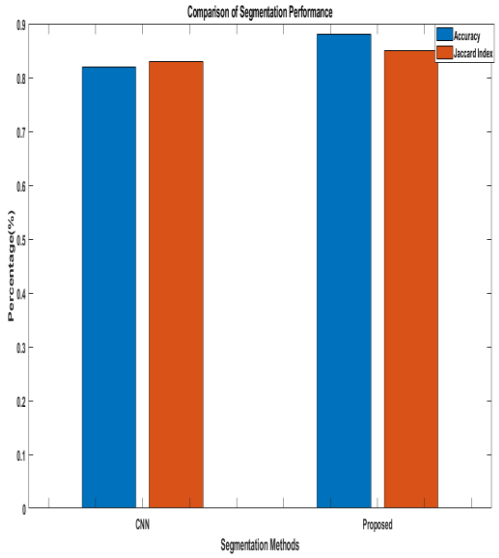


Figure-V: Comparison Chart for Segmentation Method

V. CONCLUSION

In this paper, a new segmentation technique has been proposed to segment the skin lesions automatically without any computational errors. Ensemble classifier method has been used to classify the segmented lesions in a computer aided system. Compared to the normal CAD system, the proposed CAD system outperforms well in the database called PH^2 database. This method is experimentally proved with the different segmentation results and hence proves that this method is suits for low contrast and over or under segmentation images. We believe that this method will suits well for other kinds of different medical image segmentation and classification tasks.

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