Classification of Skin Lesion by interference of Segmentation and Convolotion Neural Network

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***Abstract*— Classification of skin lesions plays a crucial role in diagnosing various, local and gene related, medical conditions in the field of dermoscopy. Estimation of these biomarkers are used to provide some insight, while detecting cancerous cells and classifying the lesion as either benign or malignant. This paper presents groundwork for detection of skin lesions with cancerous inclination by segmentation and subsequent application of Convolution Neural Network on dermoscopy images. Images included in ISIC-2016 were used as dataset. Images with skin lesions were segmented based on individual channel intensity thresholding. The resultant images were fed into CNN for feature extraction. The extracted features were then used for classification by an ANN classifier. Previously, several approaches have been used for subject diagnostic with varying degree of success. However, room is still available for exploring other techniques for improving proportion of successfully detected malignant lesions. As compared to a previous best of 97%, methodology presented in this paper yielded an accuracy of 98.32%.**

Keywords*— *skin lesion, segmentation, convolutional neural network (CNN), artificial neural network (ANN), ReLU, sensitivity, specificity, accuracy

I. INTRODUCTION

Melanoma is a form of skin cancer that has proved itself to be quite fatal. It is the reason behind 75% of the deaths caused by skin related diseases, and these numbers are getting worse with the passage of time [1]. It is annually estimated that 5 million lives are affected by skin cancer in the United States [2, 3], and 9,000 lives are annually claimed by melanoma making it a serious threat and cause for rising concern [3]. Melanoma diagnosed in early stages is the important key to stop this disease, otherwise, it becomes life threatening if not cured in early stages. This characteristic of cancer emphasizes on the importance of early and accurate diagnosis of Melanoma cancer. Although Melanoma shows visual symptoms on skin and can be identified by dermatologist, instead of using costly bulky machine relies on their experience and an unexperienced dermatologist can confuse melanoma with scars or non-lethal skin disease [4]. Another aspect to the problem statement is the increasing population of world and less dermatologist per capita to cope with this problem. Increasing the ratio of experienced dermatologist per capita is a far-fetched task and compared to that introducing an automated software-based technique to aid in this war against melanoma seems more viable [5].

Dermoscopy image is an alternative method to easily examine skin diseases. The skin images are enlarged and illuminated in the affected region of skin in order to ensure clarity and discard any skin reflection [6]. However, lack of progress in this methodology and this method relies on human vision and experience to detect disease, introducing a human error which has led to poor efficiency in melanoma detection. Efficiency of dermoscopy imagery technique can be improved by adding an automated tool to identify the anomaly of skin [7, 8]. To enhance dermoscopy image, there are many works attempted to improve the effectiveness of image segmentation technique. Multispectral imaging and confocal microcopy are widely used to address the issue of Melanoma detection. These machines are very costly and bulky. Also, special training is required to utilize this technique. Importantly, well-trained and experienced dermatologist can yield better results from this methodology [9].

Segmentation of affected skin image is a crucial process for most detection algorithm. An accurate segmentation is the first key for obtaining high accuracy of subsequent steps in the process. Several works have been attempted to extract lesion portion from the images. Garnavi *et al.* worked on segmentation of images using optimal color channels and hybrid thresholding technique for skin lesion analysis [10]. Schaefer developed segmentation on the images of lesion area by auto border detection technique [11] and extracted features (i.e. color, shape, and texture, were used for detection of melanoma [12]. Codella *et al.* combined support vector machine (SVM), and convolution neural network (CNN) for identification of melanoma [13]. The proposed methodology works on the combination of automated segmentation and CNN module. The presented methodology focuses on improving segmentation of an image, and then applying CNN technique specifically for enhance melanoma cancer detection.

II. DATASET

Dataset used for this study has been obtained from International Skin Imaging Collaboration (ISIC) [14]. 900 images (1024x767 pixels) acquired from ISIC 2016 were used for training. Further for training, dataset of 379 images were short listed and were labeled as training images. These images

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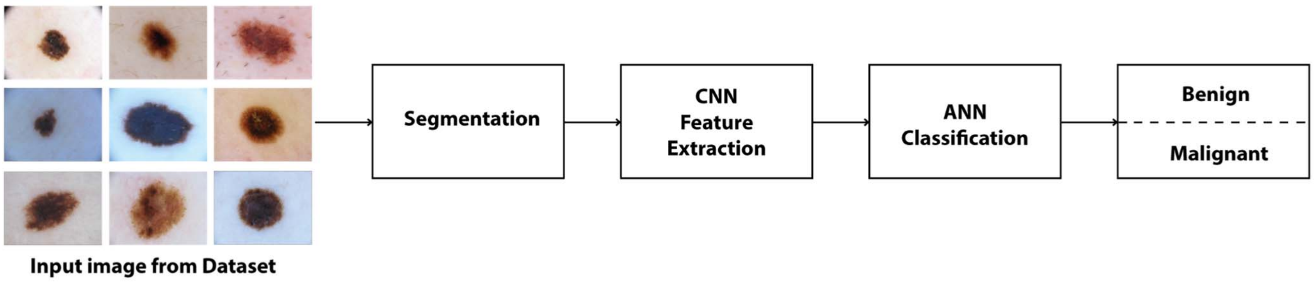

Figure 1. Implemented system flow.

were also classified on the basis of their characteristics into three types, Melanoma, Seborrheic keratosis, and Nevus. Melanoma is an image containing symptoms of melanoma cancer and we classify it in malignant category, while Seborrheic keratosis is an image of non-lethal skin disease, and nevus is an image of birthmark. The last two images are listed in benign category. Classifying of malignant and benign can help dermatologist to simplify and help deduction of the results.

III. Proposed Methodology

Automated tools for image processing were used to tackle the given problem. These tools generally works in following steps.

(1) Accurate Segmentation
(2) Feature Extraction
(3) Classification of Lesion

The flow of overall methodology is shown in Fig. 1. The images were accurately segmented for subsequent steps, and CNN was then used for feature extraction and classification. CNN can be divided into two categories: convolution layer which extract features, and ANN classifier which classifies an image. These steps will discussed in detail in following sections.

A. Segmentation

Dataset contains multiple images of malignant and benign pigmented skin lesions. A pigmented skin lesion, when referred to in dermatoscopy, is a small anomalous area on skin which is usually darker tone and has a distinguishable texture on the image, compared to the image of normal skin.

Generalized Gaussian Distribution (GGD) is the technique which is being utilized for image segmentation. All training images, were divided into its R, G and B color channels to individually determine the extent of involvement in a malignant. Intensities (I) of the malignant area was obtained, and GGD model was established. Initially, 900 training images were computed by equation 1 and 2 for obtain GGD model.

$$\mu = \frac{\sum(I)}{N} \quad (1)$$

$$\sigma = \sqrt{\frac{\sum(I^2)}{N} - \mu^2} \quad (2)$$

TABLE I GGD Statistics.

Channel	Mean(μ)	Standard Deviation(σ)
Red	145.028	27.3
Green	104.53	28.77
Blue	80.3645	22.68

Table 1 shows the statistic results for developing GGD model. These values were used to substitute in (3), then Generalized Gaussian Distribution (GGD) can be obtained. Fig. 2 shows the distribution of GGD models of R, G and B channels.

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \quad (3)$$

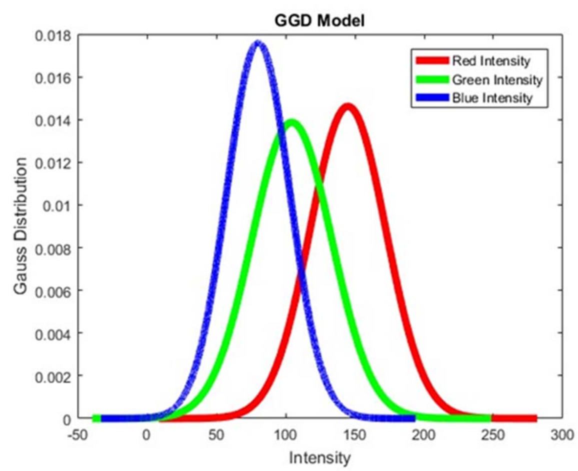

Figure 2. Proposed GGD model.

After applying GGD model on an image, morphological operation needs to be performed to remove unwanted parts. Given the fact that the image of skin lesions is darker in tone color, compared to the image of normal skin around it. Mean and standard deviation of the latter known, a generated mask must satisfy equation (4).

$$\mu - I \geq \sigma \quad (4)$$

Fig. 3 illustrates the proposed process for the segmentation of images.

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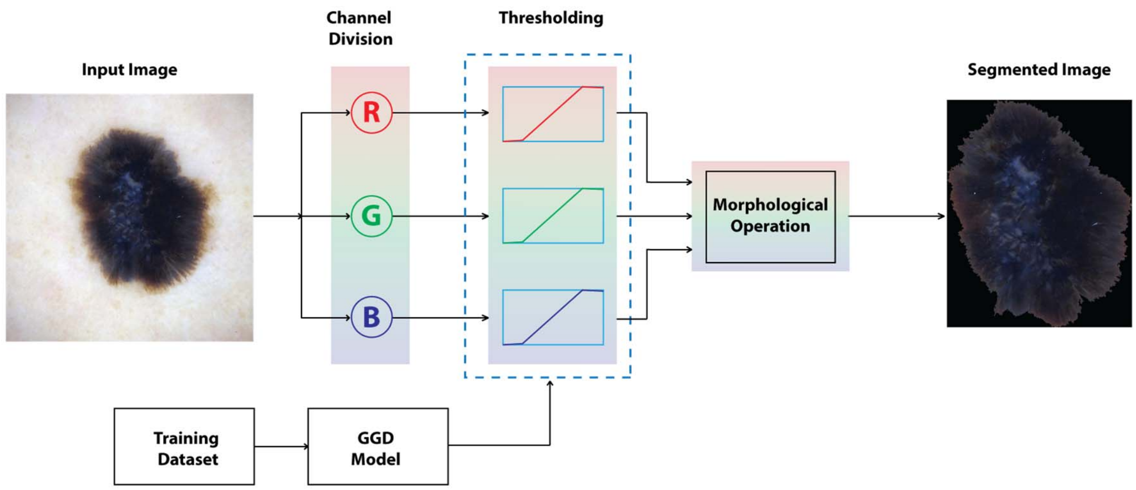

Figure 3. Segmentation methodology

B. Convolution Neural Network

CNN has proven to be quite successful in classification problems of images. It is an excellent tool for learning local and global data by combining simple features like edges and curves to give more complex features like corners and shapes. CNN was implemented for detecting melanoma cancer. Since the image of melanoma cancer has no distinct feature, therefore, deep layer CNN cannot perform well for melanoma cancer detection due to overfitting problem. This problem arises when the model is trained too well. Consequently, it starts to have deleterious effect on the results. It is suggested that CNN architecture is more suitable for identifying texture-based images and it can avoid overfitting problems.

1) *CNN Architecture*: the layout of the network used in this study is illustrated in Fig. 3. RGB channel input of skin image was normalized with zero mean and unit variance. This normalized matrix was fed into the convolution layer. Convolution layer is the first layer that convolves 16 different kernel of 7x7 pixels to give 16 different output channels. The extracted feature channels were fed into pooling layer for reducing the dimension of these channels, or it might be referred as sampling. These sampled channels were used as inputs for the next layers, called fully connected layers.

We used three-layer connected model for image classification. Each subsequent layer can reduce the number of connected neurons (i.e. 100, 50, 5 respectively). In contrast to the DCNN, we have used single convolution layer since there are few features to be learned, hence it can reduce the complexity of the CNN and avoid overfitting problem. Overview of each layer of CNN is mentioned as follows.

2) *Convolution Based Feature Extraction*: convolution layer is the most important layer in CNN and was normally used for feature extraction from the image. One or more than one 2D channels were treated as inputs to the convolution layers. These channels were convolved with different kernels. Each kernel has its own weights and represents a local feature extractor. Kernel is used to extract output features that may or may not match with the dimension of the inputs. The feature outputs contain the required features of the input image. Pooling layer plays an important role in reducing the dimensions of features. We have applied pooling layer with the kernel of 2x2 pixels. This kernel down samples the input by selecting maximum value from every consecutive 2x2 pixels of the inputs. These output channels will have half of the samples, and our computation will become less complicated. Fully-connected layers consist of neurons that connect every neuron from previous layers to every neuron in the next layer. This way we deduced results since every neuron is connected to every result in previous layer, we get collective assessment of every feature extracted from the image.

3) *ANN Classification*: CCN does not require any additional classifier like SVM, KNN since 3 fully-connected layers were used for training the classification model. Three-layer ANN classifier was used in our methodology. This type of classification brings its own unique benefits, like it is possible to apply back-propagation algorithm, which adjusts the parameters of neurons in all layers to obtain better classification model. For neuron activation, nonlinear functions were used in ANN [15].

In this CNN model, non-linear ReLU was used as activation function. ReLU is a simple function as shown in equation (5). Compared to other activation functions like Sigmoids and tanh, ReLU does not have gradient vanishing problem, which is an important factor to consider a gradient dependent machine learning process, such as implemented by this study. Rectified linear function (ReLU) due to its simplicity and gradient pre-service improves both learning speed and performance of our CNN by 2.3.

$$F(k) = \begin{cases} k, & \text{if } k > 0. \\ 0, & otherwise. \end{cases} \tag{5}$$

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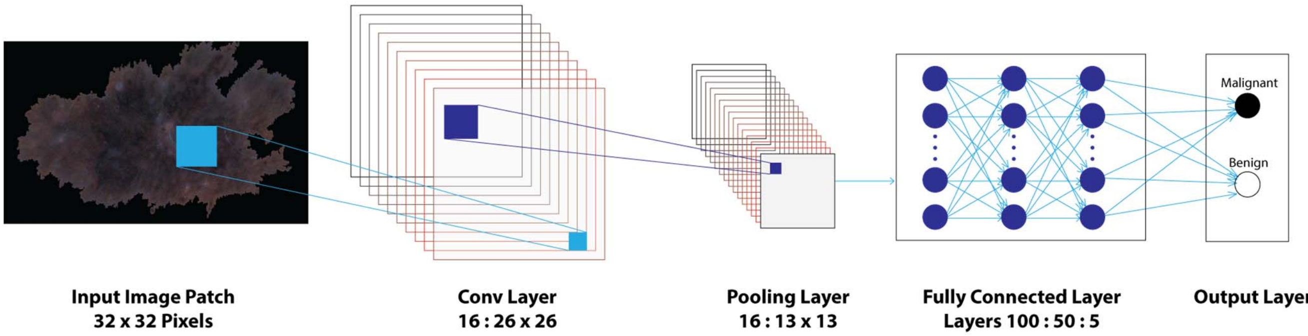

Figure 4. Proposed CNN architecture

IV. RESULTS

The performance of proposed methodology were evaluated in terms of sensitivity (6), specificity (7), and accuracy (8). Testing dataset of ISIC 2016 was used for this purpose, where 379 images were available for testing.

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{8}$$

Where,

TP = True Positive TN = True Negative
FN = False Negative FP = False Positive

TABLE II COMPARISON WITH LATEST OTHER TECHNIQUES

Algorithm	[16]	[17]	[18]	Proposed
Sensitivity	85.71	96	-	98.15
Specificity	81.25	97	-	98.41
Accuracy	82	97	85	98.32

As shown in Table II, the proposed methodology has achieved better results on the basis of selected criteria, compared with previous methodology [16-18]. The proposed model has 98.15% of sensitivity to classify malignant images, and 98.41% of specificity representing the correct rejection of benign images. Overall accuracy achieved by the proposed methodology is 98.32%, which is higher than the previous attempts [16,17,18]. This may be that the methodology proposed in this study emphasizes on both segmentation and CNN accuracy. Accuracy of whole methodology is primarily based on accurate image segmentation, as a result, an increasing of classification accuracy by CNN is obtained.

V. CONCLUSION

In this paper, methodology was proposed to detect melanoma cancer using CNN architecture. Dataset acquired from ISBI2016 was divided into two categories (melanoma and non-melanoma images). Custom made automated segmentation was applied for this specific problem, also new approach was devised for implementation of the CNN methodology. CNN was used to extract the image features and ANN was also used to classify those extracted features. ANN consisted for three-fully-connected layers. Results acquired from the proposed methodology yielded sensitivity of 98.15%, specificity of 98.41%, and accuracy of 98.32%. These figures showed improved results as compared to previous methodologies. Better results in this study were acquired as the proposed methodology emphasizes on both segmentation and CNN accuracy. Accuracy of whole methodology is primarily based on accurate segmentation of image. This leads to high classification accuracy.

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