MELANOMA DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: **Skin malignancy is the most widely recognized sort of disease, which affects the life of people every year. The detection of skin disease in the beginning periods is a difficult and costly procedure. Having an automated technique for melanoma identification will help dermatologists in the early analysis of this kind of skin malignancy. In the last few years, significant advancements have taken place in the domain of computer vision. With the advent of new algorithms, it has become possible to differentiate between clinically similar skin conditions. In this paper, a technique for detecting skin lesion images into Malignant and Benign categories is implemented by utilizing Convolutional Neural Networks (CNNs). The Convolutional Neural Network is trained to detect the injuries to a high level of exactness.**

Index Terms **–Malignant, Benign, Computer Vision, Convolutional Neural Networks.**

I. INTRODUCTION

Melanoma is a fatal form of skin cancer which is often undiagnosed or misdiagnosed as a benign skin lesion. There are an estimated 76,380 new cases of melanoma and an estimated 6,750 deaths each year in the United States. Early detection is imperative: the lives of melanoma patients depend on accurate and early diagnosis. Physicians often rely on personal experience and evaluate each patient's lesions on a case-by-case basis by taking into account the patient's local lesion patterns in comparison to that of the entire body.

One of the clinical methods used in identifying melanoma is the ABCD rule. The ABCD rule was introduced in 1985 as a method to diagnose melanoma. The ABCD acronym stands for Asymmetry, Border irregularity, Color and Diameter. The letter E was added to the ABCD acronym in 2004 which stands for evolving. Dermatologists use these parameters to identify melanoma. Each criteria has certain features that are recognized to classify melanoma into benign and malignant.

The ABCD method, in some cases, wasn't helpful to classify malignant and benign skin moles. In addition, the method couldn't recognize some malignant moles at early stages, for example malignant melanoma with a small diameter. It adds that although clinical methods have improved discrimination, they haven't removed the challenge of differentiating malignant melanoma and nevi (birth marks). Many learning approaches attempt to extract features from the data images as a step prior to image classification, while CNNs are capable of learning all the details without engineering the features.

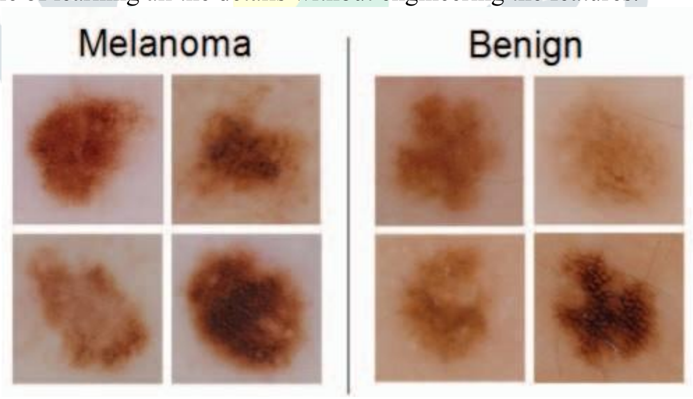


Fig. 1. Melanoma and benign skin images [2]

One of the challenges of visual screening is the visual similarity between skin diseases. Extensive analysis needs to be performed to identify the category of the lesion. Traditionally, an image using a special device, known as a dermatoscope, is taken to study the lesion closely. Unfortunately, dermatoscopes are expensive and not widely available with dermatologists. These algorithms do not require the images to be taken from special purpose devices, such as dermatoscopes, and can be applied on images obtained from general purpose cameras. In this paper we aim to take advantage of deep learning methods to form an automatic diagnosis system for melanoma detection.

Automated analysis of pigmented lesions is a growing research topic that aims to develop tools for computer aided diagnosis of skin cancer. This can be applicable in web based and mobile application as a telemedicine tool and also as a supporting system that assists physicians. Computerized diagnosis is a rising need due to increasing rate of incident, subjectivity of procedure and time and cost expenses [1].

II. METHODOLOGY

The skin lesion images are classified into melanoma or not by adopting the convolution neural network technology. The processes like lesion segmentation or complex image pre-processing are not been applied to classify whether the image is Melanoma or not.

2.1 Image pre-processing

Simple image pre-processing techniques are applied automatically to every image in the dataset before feeding the images into convolutional neural network for classification. Every image in the dataset is resized to a size of 224×224. Normalized data is obtained by subtracting the mean making the data to be zero-centered.

2.2 Convolutional Neural Network Architecture

In this section, details of the proposed CNN are discussed. Extracting an effective and discriminative feature set, which precisely differentiate between various classification groups, is a challenging task. In the one hand, there is a pitfall that if we use a large set of features, we may feed some incoherent traits to the network. On the other hand, if we use a small set of features, there is a possibility of missing some proper descriptors. Hence, automatic feature extraction systems could be an excellent choice to achieve a discriminative feature set based on labeled training set, instead of extracting the features manually which makes the process to be challenging. In this paper a deep learning framework, Convolutional neural network is used to detect melanoma automatically. CNN, a form of an artificial neural network takes advantage of a set of powerful convolve-filters which form the convolutional layers also called hidden layers. The dataset id prepared for melanoma detection to achieve good performance Afterward, the images are fed to layers of CNN architecture to classify the input as melanoma or benign.

We have to specify the number of filters to be used in each convolutional layer. These convolutional layers are responsible for detecting the patterns of images like shapes/curves, multiple edges, texture, object etc,.CNNs takes advantage of a set of powerful convolve-filters. They examine various structures and patterns in input images of data set. Hence, in utilization of CNN, the input is the image itself and the network automatically extracts appropriate aspects of the image.

Conventional CNNs are known to contain several convolve and also pooling layers and a fully connected layer will be the part of the last layer. Convolve layers are used to filter the input images making use of a set of kernels of desired size. Usually each convolve layer is followed by a pooling layer. The pooling layer reduces the size of the feature map by selecting the maximum or mean values, in each defined window. The pooling layer helps to recognize some general patterns in the images. These general patterns are perceptible in resized image.

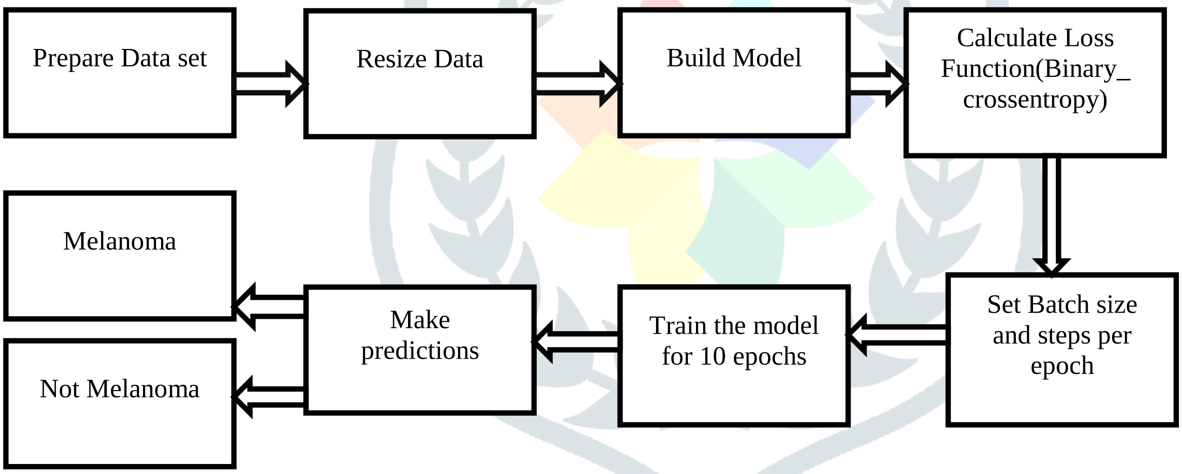


Figure 2.1: Block Diagram for Detection of Melanoma using CNN

In the proposed architecture the Convolutional Neural Network has Convolution layer, activation layer, pooling layer, dropout layer and fully connected layer. The filter sizes for the convolutional layers are as follows: The convolutional layers are 3 × 3 with padding of 2. All the convolutional layers have a stride of 1. Filter's weights are initialized using random numbers with zero mean and standard deviation of one. The weights of the filter are multiplied by one over the square root of the size of the input image and the number of convolutional kernels in each convolutional layer.

The initialization method used can be described by the following equation:

$$Wij = U[-1/\sqrt{n}, 1/\sqrt{n}] \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

W is the wieghts at each layer
U is a uniform distribution on a specific interval
n is the previous layer's size.

The pooling layers have a stride of 4 and the dropout layers have a hyper parameter P, called the dropout rate which determines the amount of dropped out units. The dropout rate used is 0.5. The output layer used for classification is the sigmoid classifier. The weight, input and the bias of output function is computed during the gradient descent learning process. A loss function measures the difference between the correct output and the produced output by the algorithm.

The aim of the learning process is to minimize the loss function by obtaining the value of the weights. Once we get the validation accuracy and training accuracy for all epochs, the best training model will be saved and using the best model the presence of melanoma will be predicted for the test dataset total of 36 images belonging to two classes.

III. Experimental Results

In this section the proposed method for Melanoma Detection is evaluated on the available dataset of skin lesion images. The dataset should be prepared such that the model will not be trained heavily on particular type of images. To perform training, validation and testing the dataset is split into three distinct groups. Each group of dataset is sub grouped into two classes namely melanoma and non-melanoma categories. Thus forming a total of six distinct classes. There should not be any similar images between the training and testing dataset to evaluate the model for never before seen images.

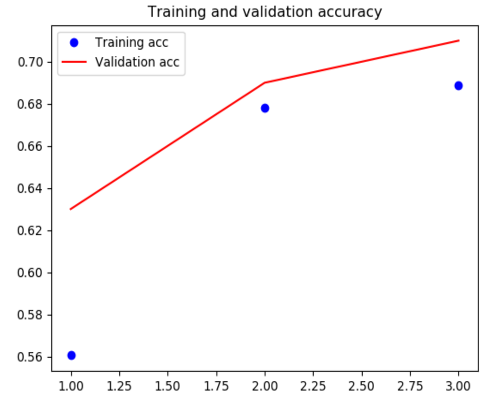


Figure 3.1: Training and validation accuracy

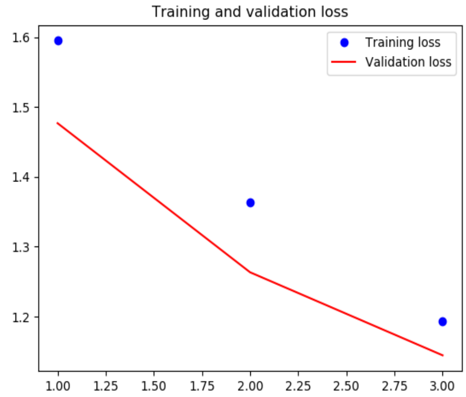
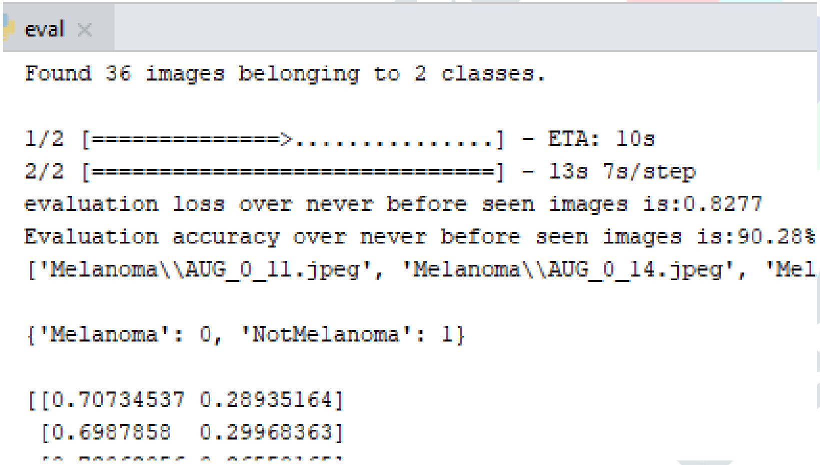


Figure 3.2: Training and validation loss

As seen in the figure 3.1 and figure 3.2 the validation accuracy of 74% is obtained and validation loss achieved is 0.8 for the architecture of convolutional neural network implemented. Accuracy of 90.28% and loss of 0.8 is obtained for the set of test images and the snapshot of evaluation accuracy and loss obtained is shown in figure 3.3. False Positive images are those which belong to positive class and predicted incorrectly. Similarly False Negative images are those which belong to negative class and predicted incorrectly. Sample of images for which false negative and false positive result obtained is shown in figure 3.4 and figure 3.5 respectively.



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eval
Found 36 images belonging to 2 classes.

1/2 [==============>...............] - ETA: 10s
2/2 [==============================] - 13s 7s/step
evaluation loss over never before seen images is:0.8277
Evaluation accuracy over never before seen images is:90.28%
['Melanoma\\AUG_0_11.jpeg', 'Melanoma\\AUG_0_14.jpeg', 'Mel

{'Melanoma': 0, 'NotMelanoma': 1}

[[0.70734537 0.28935164]
 [0.6987858  0.29968363]
```

Figure 3.3: Evaluation accuracy 90.28% and loss 0.8

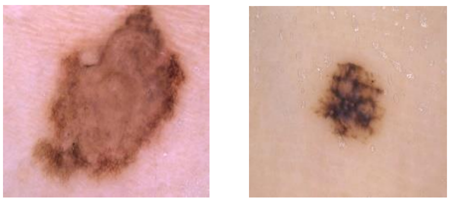

Figure 3.4: False Negative images

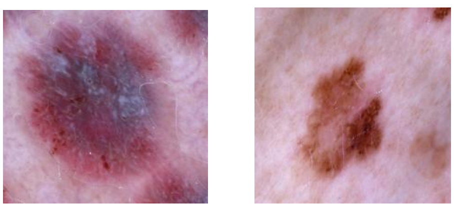

Figure 3.5: False Positive Images

IV. Conclusion

Non-dermoscopic images captured from digital cameras are serving as a tool in telemedicine for melanoma detection. In this paper a deep learning, computational complex method was implemented which makes use of clinical images. With the implementation using convolutional neural networks the system is able to detect melanoma cases from benign cases. For training, we used an available small dataset. By cropping, scaling, and rotating of images the number of images was increased. The proposed method left the process of feature extraction to CNN while traditional learning approaches try to extract features from data.

References

[1] E. Nasr-Esfahani, S. Samavi, "Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network", 978-1-4577-0220-4/16/$31.00 ©2016 IEEE.

[2] International Symposium on Biomedical Imaging (ISBI) 2016 challenge "iSBI 2016: Skin Lesion Analysis Towards Melanoma Detection Part 3: Lesion Classification".

[3] Aya Abu Ali and Hasan Al-Marzouqi, "Melanoma Detection Using Regular Convolutional Neural Networks", 2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA).

[4] I. Giotis, N. Molders, S. Land, M. Biehl, M. F. Jonkman and N. Petkov, "MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images," Expert Systems with Applications, Elsevier, vol. 42, no. 19, pp. 6578-6585, 2015.

[5] The American Cancer Society medical and editorial content team,"Survival Rates for Melanoma Skin Cancer, by Stage", Available at:[https://www.cancer.org/cancer/melanoma-skin-cancer/detectiondiagnosis-staging/survival-rates-for-melanoma-skin-cancer-bystage.html],May 19, 2016.

[6] Naheed R. Abbasi, Helen M. Shaw, Darrell S. Rigel, Robert J. Friedman, William H. McCarthy, Iman Osman, Alfred W. Kopf, David Polsky , "Early Diagnosis of Cutaneous Melanoma Revisiting the ABCD Criteria", American Medical Association ,Vol. 292, No. 22,December 8, 2004.

[7] Krizhevsky, A., Sutskever, I., Hinton, G."ImageNet classification with deep convolutional neural networks", In Proc. Advances in Neural Information Processing Systems 25 10901098 (2012).

[8] Ashfaq A. Marghoob1, Alon Scope "The Complexity of Diagnosing Melanoma", Journal of Investigative Dermatology (2009), 129, 1113. doi:10.1038/jid.2008.388.

[9] D.Ciresan, U.Meier,and J.Schmidhuber, "Multi-column deep neural networks for image classification," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2012, 2012, pp. 3642-3649.

[10] Suk, Heung-Il, and Dinggang Shen, "Deep learning-based feature representation for AD/MCI classification," Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013. Springer Berlin Heidelberg, 2013. 583-590.

[11] F. Nachbar, W. Stolz, T. Merkle, A. B Cognetta, T. Vogt, M. Landthaler, P. Bilek, O. B.-Falco, and G. Plewig, "The abcd rule of dermatoscopy: high prospective value in the diagnosis of doubtful melanocytic skin lesions," Journal of the American Academy of Dermatology, vol. 30, no. 4, pp. 551–559.

[12] N. F. M. Azmi, H. M. Sarkan, Y. Yahya and S. Chuprat, ABCD Rules Segmentation on Malignant Tumor and Benign Skin Lesion Images, 2016 3rd International Conference on Computer and Information Sciences (ICCOINS), Kuala Lumpur, 2016, pp. 66-70.