
A Novel Approach for Detection of Skin Cancer using Back Propagation Neural Network

Ms. Jignyasa Sanghavi

Department of Computer Science & Engineering, Shri Ramdeobaba College of Engineering & Management,
Nagpur

Email: sanghavijb1@rknec.edu

Received: 06th October 2019, Accepted: 20th November 2019, Published: 31st December 2019

Abstract

Skin cancer is one of the most occurring cancers in the western countries. In US, millions of patients are reported for skin cancer. There are two main types of skin cancer Melanoma and Non melanoma skin cancer. The non melanoma skin cancer are reported occurring due to the exposure of skin to harmful ultra-violet (UV) rays, the rays internally disturbs the skin cell structure, causing malfunctioning of the skin cells. Early detection of skin cancer can reduce the mortality rate of skin cancer. Considering the seriousness of this domain, we tried to develop a system which will automatically detect the Melanoma skin cancer from skin lesion images. Advanced Imaging techniques are used for pre-processing, segmentation and feature extraction. Back propagation Neural network is used for classification. However now a days Deep neural networks are on boom, but they require huge data for training the networks. In medical domain such a huge data is not available for training. On comparison with the results of the proposed system with some standard classifiers, we observe that the hybrid neural network classifier improves the accuracy by 15%.

Keywords

Skin Cancer, Computer Aided System, Saliency Map, Back-propagation

Introduction

Skin cancer is curable if detected at early stage. Like many cancers, a skin cancer begins with normal visible lesions. These lesions are changes in skin that are not cancer, but can become cancer over time. According to the article of Forbes, the nations which are influenced by ultraviolet radiations are United States, Canada, Cuba, parts of the Pacific and Northern Europe, South Asian nations, including India, Maldives, Bhutan and Bangladesh [1].

Skin cancer can be mainly categorized as three types such as Basal cell carcinoma (BCC), Melanoma, and Squamous cell carcinoma (SCC). The non-melanomas include BCC and SCC. BCCs are uncontrolled growth of lesions that rise in basal cells in the skin. Squamous-cell carcinoma (SCC) is a cancer which occurs in squamous cell. It spreads faster to other parts in the body. The lethal form of skin cancer is melanoma which arises in the melanocytes cell. The patients recovered from melanoma if it was diagnosed and treated in early stages.

Many researchers tried to give solution for detection of Skin cancer using Image processing. The traditional method is consulting dermatologist. To develop the accurate system for skin cancer detection, sequencing of processing blocks is arranged according to methods of detection of dermatologist is following. Generally the steps followed are Pre-processing for noise removal, segmentation of region of interest, Feature extraction, training of classifier and finally classification. In the following section we tried to present the review of the researchers who worked on skin cancer detection using image processing, followed by the proposed method and its comparison with some standard classifiers. At last concluded with some interesting observations about the proposed classifier, and suggest ways on how it can be improved further.

Literature Survey

Diagnosis of an obscure skin lesion is critical to empower appropriate medications. Early detection of melanoma reduces the mortality rate. Previously neural networks and machine learning algorithms were used for classification. Features were given as input to the classifiers. A system proposed [2], outline a framework for the detection of melanoma using ABCD features: Asymmetry, Border, Color, and Diameter (ABCD of melanoma) and neural network system for grouping various types of moles. Same features were used in the system [5], for the detection of Melanoma Skin Cancer using Image Processing apparatus. The authors claimed that this instrument is more valuable for the rustic territories where the specialists in the medicinal field may not be able to access. Feature extraction is very important phase in classification if machine learning algorithms or any classifiers are used. Some of the feature extraction techniques are common in many papers of image processing are proved to be very efficient for achieving high

accuracy. Some of them are Saliency Map, Daubechies wavelet, Local binary Pattern, Fourier descriptors, GLCM, etc. [15, 16]. Some considered the color features and wavelet features for classification of benevolent and malignant melanomas [3]. In the framework [4], for classification they used SVM for early detection of skin cancer. Other author[6] used bolster vector machine with Gaussian spiral premise piece (SVM-RBF) for the classification of cancerous "malignant" or non-cancerous mole "generous". A non-intrusive robotized skin lesion investigation framework for the early detection of melanoma [10] utilized image processing procedures and portable innovations. The test result is assessed on PH2 database from Pedro Hispano healing centre.

Looking at the limitation of classifiers for large feature sets then came the era of Deep Neural networks. The deep neural networks require huge data for the training the network. In the research work [7], dataset of 129,450 clinical images were used for implementing Deep convolutional neural networks (CNNs) for classifying two basic paired cases: keratinocyte carcinomas versus kind seborrheic keratoses; and malignant melanomas versus kind hearted nevi. In the examination[8] two deep learning strategies: Lesion Indexing Network (LIN) and the Lesion Feature Network (LFN) were used for Lesion Segmentation, Lesion Dermoscopic Feature Extraction, and Lesion Classification using ISIC 2017 dataset. The openly accessible databases ISBI 2016 and the PH2 database were used to implement 19-layer deep convolutional neural networks (CNNs) for skin lesion division [9]. In the exploration [11], deep convolutional neural networks (CNNs) in contrasted with existing strategies were used for highlighting sectioned outcome. For assessment, author have used ISBI 2016 Skin Lesion Analysis towards Melanoma Detection Challenge dataset. A deep Siamese CNN (SCNN) design was introduced [12], which can be prepared with just parallel image match data to learn image portrayals with less supervision. The author's observation showed that author's framework with 10 deep SCNN is practically identical to the cutting edge single administered CNN, and requires significantly less supervision for preparing. In [13], Deep Convolutional Neural Network (CNN) Framework was implemented utilizing the 23,000 skin sickness images from the Dermnet dataset. They tested the execution with Dermnet and OLE dataset with accuracy of 73.1%. Deep Learning networks in combination with machine learning algorithms for melanoma skin cancer detection utilizing dataset of 900 training and 379 testing images[14].

Proposed System for Automatic Detection of Skin Cancer

The figure 1 shows the flow of proposed system. Like all the automatic diagnosis system this system is also divided into four phase: Pre-processing, Segmentation, Feature Extraction and Classification.

Pre-Processing

This phase includes hair removal block by detecting the edges using canny edge detection algorithm. An adaptive median filter is applied in 2-3 iterations to remove the hairs. Gaussian Filter is used for retaining the sharpness of the image.

Segmentation of Region of Interest

Saliency map detection algorithm is used for segmentation. The hair removed regions are then given to a saliency map detection block. The saliency map works using the following steps:

- Represent the image in hyper-complex representation with the help of image entropy. Quaternion function is used to represent image in hyper complex representation.
- Apply Gaussian filter to the entropy values and evaluate the maximum entropy regions.
Entropy = $-\sum h(j) \ln(h(j))$ where j is an image.
- Again apply Gaussian filter to the maximum entropy regions in order to smooth the regions and obtain a rough saliency map.

$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

- Evaluate the mean of rough saliency map, and use it for thresholding.
- Use this mask as a filter and apply it on the input image to get the saliency map image.

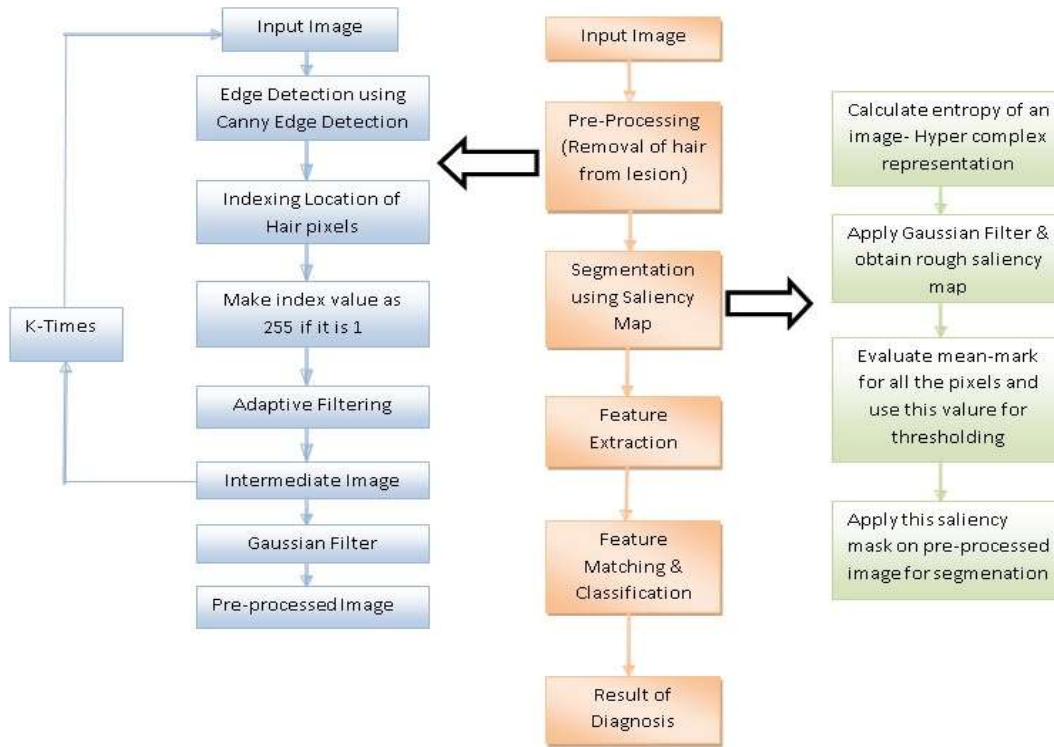


Figure 1: Proposed System

Feature Extraction

Features generally used for classification are based on color, shape and texture[17]. Based on the experimental observations following features from color, shape and texture domain are selected in this phase.

Sr.No.	Feature	Description
Features based on Shape		
1	Circularity	$4\pi A/l^2$
2	Solidity	$\frac{4A}{\pi d^2} / \sqrt{\frac{4A}{\pi d}}$
3	Aspect Ratio	Width / Length
4	Shape Skewness	$\frac{M_3}{(M_2)^{3/2}}$ M2 is Variance and M3 is third Moment
Features based on Color		
5	High Luminance Scale	Highest Scale value extracted using SIFT algorithm
6	Entropy	$-\sum h(j)\ln(h(j))$
Features based on Border		
7	Fast Corners	Corners extracted using FAST algorithm(Fast Accelerated Segment Test)
8	Boundary Skewness	Same as shape skewness but on border

Table 1: Features Extracted for Classification

Classification & Output

In the classification phase the features extracted given in table 1 are given as an input to the classifier to categorize among two classes Cancerous or Non- cancerous based on the features. The multi-layer neural system (MNN) Back-propagation (BP) is used for training the system. Learning in the system is accomplished by limiting the least square

contrasts between the ideal and the figured yields to make an ideal system to best inexact the info yield connection on the confined space secured by the preparation set. A common three-layer neural system framework with four info hubs in the information layer, 10 concealed hubs in the shrouded layer, and 5 yield hubs in the yield layer frequently noted as 4 - 10 – 5 are used in the proposed system. All hubs in various layers are associated by related loads. For each info design displayed to the system, the present system yield of the information design is registered utilizing the present loads. At the subsequent stage, the outliers or distinction between the system yield and expected yield will be backpropogated to alter the loads between layers in order to draw the system yield nearer to the ideal yield. The objective of the system is to reduce the false positive detection. Here, the classification step is divided into two phases.

Training Phase: During the training phase system was trained with 60% of the images of the dataset.

Testing Phase: During the testing phase remaining 40% image which was not given for training is given to the classifier to test the performance of the system.

Result Analysis

For the effective accuracy, we took nearly 400 images of both cancerous and non-cancerous. The images were divided into 60:40 ratio, where in 240 images were kept for training and the remaining 160 images were kept for testing.

Number of images trained	Number of images tested	Correctly Classified images	Accuracy (%)
240	150	134	89

True positive (TP)	True negative (TN)	False positive (FP)	False negative (FN)
133	17	9	8

Table 2. Performance and Accuracy of Classification

Some of the result simulations are shown below:

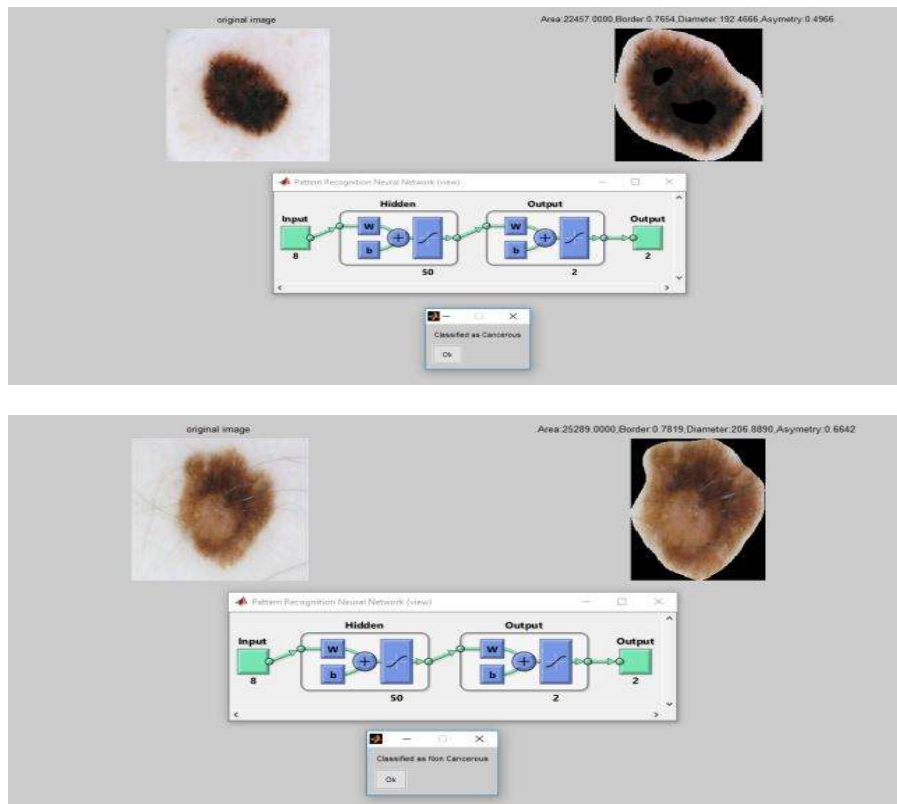


Figure 2: Simulation (a) Image Classified as Cancerous (b) Image Classified as Non-Cancerous.

Conclusion & Future Work

From the proposed work we conclude that the Backpropagation neural network based implementation is efficient method for skin cancer detection if more dataset is not available for training deep networks. It can perform better, and thus can be used as second opinion by health practioners for skin disease detection. As an extension to this work, the patients' history can be inculcated with this system so as to give more accurate results.

Acknowledgement

I am thankful to International Skin Imaging Collaboration for providing the skin cancer dataset at ISIC platform.

References

- [1] Allison Van Duden, "World's Skin Cancer Hot Spots", <https://www.forbes.com/>, Last accessed 8/10/2019.
- [2] Wilson F. Cueva, F. Muñoz, G. Vásquez., G. Delgado, "Detection of skin cancer "Melanoma" through Computer Vision", Proceedings of XXIV International Conference on Electronics, Electrical Engineering and Computing (INTERCON), IEEE 2017.
- [3] Farzam Kharaji Nezhadian, Saeid Rashidi, "Melanoma skin cancer detection using color and new texture features", Proceedings of Artificial Intelligence and Signal Processing (AISP), IEEE 2017.
- [4] Uzma Bano Ansari, Tanuja Sarode, "Skin Cancer Detection Using Image Processing", International Research Journal of Engineering and Technology (IRJET), Volume: 04, Issue: 04, Apr-2017.
- [5] Shivangi Jain, Vandana Jagtap, Nitin Pise, "Computer aided Melanoma skin cancer detection using Image Processing", Proceedings of International Conference on Intelligent Computing, Communication & Convergence (ICCC-2015), Elsevier – 2015.
- [6] Suleiman Mustafa, Akio Kimura, "A SVM-based diagnosis of melanoma using only useful image features", 2018 International Workshop on Advanced Image Technology (IWAIT), IEEE 2018.
- [7] Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun, "Dermatologist-level classification of skin cancer with deep neural networks", Vol 542, p-115- 127, Springer Nature Feb-2017.
- [8] Yuexiang Li, Linlin Shen, "Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network", p-1-16 Sensors 2018.
- [9] Yading Yuan, Ming Chao, Yeh-Chi Lo, "Automatic Skin Lesion Segmentation Using Deep Fully Convolutional Networks with Jaccard Distance", IEEE Transactions on Medical Imaging, Volume: 36, Issue: 9, Sept. 2017.
- [10] Supriya Joseph, Janu R Panicker, "Skin Lesion Analysis System for Melanoma Detection with an Effective Hair Segmentation Method", IEEE International Conference on Information Science (ICIS), IEEE Aug-2016.
- [11] Lequan Yu, Hao Chen, Qi Dou, Jing Qin, Pheng-Ann Heng, "Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks", IEEE Transactions on Medical Imaging, Volume: 36, Issue: 4, April 2017.
- [12] Yu-An Chung, Wei-Hung Weng, "Learning Deep Representations of Medical Images using Siamese CNNs with Application to Content-Based Image Retrieval", Proceedings of 31st Conference on Neural Information Processing Systems (NIPS 2017).
- [13] Haofu Liao, "A Deep Learning Approach to Universal Skin Disease Classification", Graduate Problem Seminar - Project Report, University of Rochester, 2015.
- [14] N. C. F. Codella, Q.B. Nguyen, S. Pankanti, D. A. Gutman, B. Helba, A. C. Halpern, J. R. Smith, "Deep learning ensembles for melanoma recognition in dermoscopy images", IBM Journal of Research and Development, Volume: 61, Issue: 4/5, July-Sept. 2017
- [15] J. Sanghavi, D.Kayande, "Content based Image Retrieval (CBIR) System for Diagnosis of Blood Related Diseases", National Conference on Innovative Paradigms in Engineering & Technology (NCIPET-2013) Proceedings published by International Journal of Computer Applications® (IJCA),2013.
- [16] Sneha Ghonge, Jignyasa Sanghavi, "Classification of Motorcyclists without Helmet via Daubechies Wavelet Transform and SVM", Helix Vol. 8(5): 3998- 4001 DOI 10.29042/2018-3998-4001, August 2018.
- [17] Vedanti Chintawar, Jignyasa Sanghavi, "A Review on Computer-Aided Melanoma Skin Cancer Detection using Image Processing", EasyChair Preprint no. 584, October 2018.