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# SKIN CANCER DETECTION USING AI BASED ON DESIGN THINKING

**Ashok Kumar.R[1],Dr.P.Sumathi[2], Akshaya.J*, Ashwanth Raj.T*, Kandhakrishnan.N*,Nandhini.V*,**
Assistant Professor[1], Head of the Department[2], Student*,
Department of Information Technology,
SNS College of Engineering Coimbatore, India.
Hod.it@snsce.ac.in ,achujaga2709@gmail.com , ashwanthraj9669@gmail.com ,

kandhakrishnan2000@gmail.com , nandhinivijiyakumar0804@gmail.com .

**ABSTRACT** :
Skin cancer is an alarming disease for mankind. The necessity of early diagnosis of the skin cancer have been increased because of the rapid growth rate of Melanoma skin cancer, its high treatment costs, and death rate. This cancer cells are detected manually and it takes time to cure in most of the cases. This project proposed an artificial skin cancer detection system using image processing and artificial intelligence method. The features of the affected skin cells are extracted after the segmentation of the dermoscopy images using feature extraction technique. A deep learning-based method convolutional neural network classifier is used for the stratification of the extracted features.

## I. INTRODUCTION

Automated skin lesion classification in dermoscopy images is an essential way to improve the diagnostic performance and reduce melanoma deaths. Automatic localization of skin lesions within dermoscopy images is a crucial step toward developing a decision support system for skin cancer detection. However, segmentation of the lesion image can be challenging, as these images possess various artifacts distorting the uniformity of the lesion area. Recently, deep convolution learning-based techniques have drawn great attention for pixel-wise image segmentation. These deep networks produce coarse segmentation, and convolutional filters and pooling layers result in segmentation of a skin lesion at a lower resolution than the original skin image. To overcome these drawbacks, the proposed system uses a super pixel-based fine-tuning strategy to effectively utilize the characteristics of the skin image pixels to accurately extract the border of the lesion. The proposed approach not only learns a global map for skin lesions, but also acquires the local contextual information, such as lesion boundary. It can, therefore, accurately segment lesions within a given skin image, even in the presence of fuzzy boundaries and complex textures**.**

## II.BACKGROUND

A skin lesion is a part of the skin that has an abnormal growth or appearance compared to the skin around it. Two categories of skin lesions exist: primary and secondary. Primary skin lesions are abnormal skin conditions present at birth or acquired over a person's lifetime. Secondary skin lesions are the result of irritated or manipulated primary skin lesions. Change of recreational behavior together with the increase in ultraviolet radiation cause a dramatic increase in the number of melanomas diagnosed. The DCNN is used for the classification task has a remarkable localization ability that can highlight the discriminative regions in images, despite being trained with only image-level labels, instead of the bounding boxes of discriminative regions. Hence, strengthening the discriminative ability of a DCNN via taking advantage of its self-attention ability. Since the higher layers in a DCNN have a better ability for semantic abstraction than lower ones, it might be possible to use the feature maps obtained by higher layers as the attention mask of lower ones. Meanwhile, the residual network is more suitable for small-sample learning problems than other DCNNs, such as AlexNet , VGG, and GoogLeNet, since it uses shortcut connections to skip one or more layers, and thus enable the construction of a deeper network. The raw input image is transformed through a multi-scale convolutional network, which produces a set of feature maps. The feature maps of all scales are concatenated, and then the coarser-scale maps are upsampled to match the size of the finest image scale map.

## III.PREVIOUS STUDY

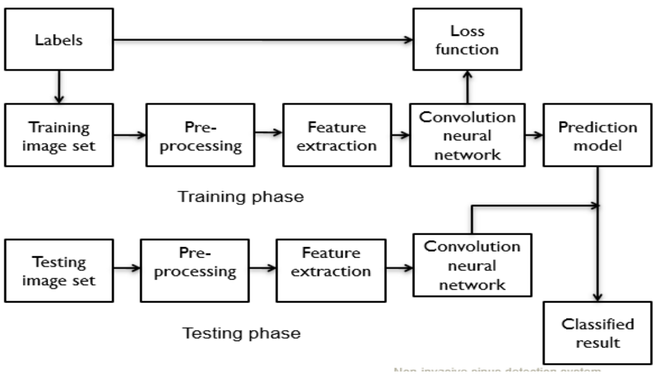
Many studies using machine learning have reported ways of classifying these ambiguous characteristics using techniques such as traditional machine learning support vector machines (SVMs), K-means clustering, naïve Bayers classifiers, etc. Traditional machine learning methods require expert knowledge and time-consuming hand-tuning to extract specific features. Therefore, with traditional machine learning, features that represent the characteristics to be extracted must be implemented using various segmentation methods: thresholding, adaptive thresholding, clustering, region-growing, etc. To overcome these limitations, deep learning (a branch of machine learning) can be used to acquire useful representations of features directly from data. Especially, the convolutional neural network (CNN) model uses a deep learning architecture to create a powerful imaging classifier. For that reason, recently, it is widely used to analyze medical images, such as X-ray, CT, and magnetic resonance imaging (MRI) images. Deep learning algorithms through millions of data points to find patterns and correlations that often go unnoticed by human experts. These unnoticed features can produce unexpected results. Particularly in the case of deep learning-based disease diagnosis with medical images, it is important to evaluate not only the accuracy of the image classification but also the features used by the model, such as the location and shape of the lesion. However, one of the limitations is that there is a lack of transparency in deep learning systems, known as the black box problem. Without an understanding of the reasoning process to evaluate the results produced by deep learning systems, clinicians may find it difficult to confirm the diagnosis with confidence. The objective of this study to investigate the ability of multiple deep learning models to recognize the features of Skin cancer in PNS X-ray images and to propose the most effective method of determining a reasonable consensus.

## IV.IMAGE LABELING AND DATASET DISTRIBUTIONS

All subjects were independently labeled as normal or SCC, BCC, Melanoma. Labeling was first evaluated with the original images on a picture archiving communication system (PACS) and secondly with the resized images that were used for the actual learning data. Datasets were defined as the internal dataset and temporal dataset, with the temporal dataset used to evaluate the test. The Internal dataset was randomly split into training (70%), validation (15%), and test (15%) subsets. The distribution of internal the test dataset consisted of 32% Normal, 32% SCC, and 34% BCC and 32% MELANOMA.

## V.BLOCK DIAGRAM

The data is being collected in the form the kaggle images that portrays the scanned parameters of skin cancer with two conditions, one is normal and another is cancer condition and the collected data are being trained with these conditions. A model file has been developed for acquiring the input image. An CNN algorithm has been applied for the image analysis with the previous data.




## VI.PREPROCESSING

Images come in different shapes and sizes. They also come through different sources. Taking all these variations into consideration, we need to perform some pre-processing on any image data. RGB is the most popular encoding format, and most natural images. Also, among the first step of data pre-processing is to make the images of the same size. Here we have used auto resizing for training to make all the images in the dataset to convert in to same resolution.

## VII.FEATURE EXTRACTION

The process of feature extraction is useful when you need to reduce the number of resources needed for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a given analysis. Also, the reduction of the data and the machines efforts in building variable combinations (features) facilitate the speed of learning and generalization steps in the machine learning process.

## VIII.CNN

In deep learning, a convolutional neural network (CNN) is a type of deep neural networks, which deals with the set of data to extract information about that data. Like images, sounds or videos etc. can be used in the CNN for the data extraction. There are mainly three things in CNN. First one is local receptive field and then shared weight and biases and the last one is activation and pooling. In CNN, first the neural networks are trained using a heavy set of data so that the CNN can extract the feature of given input. When the input is given, first image preprocessing is done then the feature extraction occurs on the basis of set of data stored and then the classification of data is done and output is shown as the result. The CNN can deal with those input only for what the neural network is trained and the data is saved. They are used in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

## IX.DATASET

One major advantage of using CNNs over NNs is that you do not need to flatten the input images to 1D as they are capable of working with image data in 2D. This helps in retaining the spatial properties of images. So here we are using x-ray data base which consist of four categories Normal, SCC, BCC, Melanoma.

## X.PRE-PROCESSING STEPS

The pre-processing steps were conducted with resizing, patch, and augmentation steps. The first pre-processing step normalizes the size of the input images. Almost all the radiographs were rectangles of different heights and too large (median value of matrix size ≥1,800). Accordingly, we resized all images to a standardized 224×224 pixel square, through a combination of preserving their aspect ratios and using zero-padding. The investigation of deep learning efficiency depends on the input data; therefore, in the second processing step, input images were pre-processed by using a patch (a cropped part of each image). A patch was extracted using a bounding box so that it contained sufficient cancer segmentation for analysis. Finally, data augmentation was conducted for just the training dataset, using mirror images that were reversed left to right and rotated −30, −10, 10, and 30 degrees.

## XI.IMAGE LABELING AND DATASET DISTRIBUTIONS

All subjects were independently labeled twice as “normal” or “Cancer” by two radiologists. Labeling was first evaluated with the original images on a picture archiving communication system (PACS) and secondly with the resized images that were used for the actual learning data. Datasets were defined as the internal dataset and temporal dataset, with the temporal dataset used to evaluate the test. The internal dataset was randomly split into training (70%), validation (15%), and test (15%) subsets.

## XII.CONCLUSION

In this project, we have proposed a reliable and robust method for skin cancer detection in highly cluttered images using CNN. The cluttered images are obtained using dermoscopy images. The image sequences also provide the candidate cancer region proposals done by multilevel graph cut. We have introduce a verification step in which the proposed region is classified into SCC,BCC,Melanoma,Normal classes, Thus, determining whether the proposed region is truly affected by skin cancer or not. We applied CNN features to machine learning algorithm to achieve better performance.

## XIII.REFERENCE

[1] R.L. Siegel, K.D. Miller, and A. Jemal. ” Cancer statistics, 2016,” CA: A Cancer Journal for Clinicians. vol. 66, no. 1, pp. 7-30, 2016.
[2] H. W. Rogers, M. A. Weinstock, S. R. Feldman, B. M. Coldiron. ” Incidence estimate of nonmelanoma skin cancer (keratinocyte carcinomas) in the US population, 2012.” JAMA Dermatol. vol. 151, no. 10, pp. 1081-1086, 2015.
[3] H. Kittler, H. Pehamberger, K. Wolff, and M. Binder. ” Diagnostic accuracy of dermoscopy,” Lancet Oncol. vol. 3, no. 3, pp. 159165, 2002.
[4] N. Codella, J. Cai, M. Abedini, R. Garnavi, A. Halpern, and J. R. Smith , ” Deep Learning, Sparse Coding, and SVM for Melanoma Recognition in Dermoscopy Images,” in Proc. MICCAI, 2015, pp. 118-126.
[5] N. C. F. Codella, D. Gutman, M. Emre Celebi, B. Helba, M. A. Marchetti, S. W. Dusza, A. Kalloo, K. Liopyris, N. Mishra, H. Kittler, A. Halpern. (Oct. 2017)” Skin Lesion Analysis Toward Melanoma Detection: A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC),” [Online].

[6] J. Weese, and C. Lorenz. ” Four challenges in medical image analysis from an industrial perspective,” Med. Image Anal., vol. 33, pp. 44-49, Oct. 2016.
[7] Y. Song, W. Cai, H. Huang, Y. Zhou, D. D. Feng, Y. Wang, M. J. Fulham, and M. Chen. ” Large Margin Local Estimate With Applications to Medical Image Classification,” IEEE Trans. Med. Imag., vol. 34, no. 6, pp. 1362-1377, Jun. 2015.
[8] T.R.Lekhaa, “Networked visual servo control using cloud computing” IJMTES june 2014.
[9] Y. LeCun, Y. Bengio, and G. Hinton. ” Deep learning,” Nature, vol. 521, pp. 436-444, 2015.
[10] M. Oquab, L. Bottou, I. Laptev, and J. Sivic , ” Learning and Transferring Mid-level Image Representations Using Convolutional Neural Networks,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2014, pp. 1717-1724.
[11] Hoo-Chang Shin, Holger R. Roth, Mingchen Gao, Le Lu, Ziyue Xu, Isabella Nogues, Jianhua Yao, Daniel Mollura, and Ronald M. Summers. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Trans. Med. Image., vol. 35, no. 5, pp. 1285-1298, May 2016.