# Skin Vision: Skin Cancer Detection Using Convolutional Neural Network

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***Abstract*—Early skin cancer identification is essential and, in certain circumstances, such as melanoma and focal cell carcinoma, it can stop the disease's progression. Nevertheless, there are a number of factors that negatively affect the detection accuracy. The usage of image processing and machine vision in the realm of healthcare and medical applications has recently increased significantly. In this study, we employ Convolution neural networks to identify and categorise the kind of cancer using clinical picture data from the past. Building a CNN model to accurately detect skin cancer with $>$80% precision is one of our research's goals. Another is to keep the prediction's false negativity rate below 5%.**

***Index Terms*—: Skin cancer diagnosis, Deep learning, Convolutional neural networks [Standard CNN],Skin cancer, Artificial neural networks.**

## I. Introduction

Skin cancer is a fatal condition. Three fundamental layers make up the skin. First-layer squamous cells, second-layer basal cells, and third-layer melanocytes make up the skin's outermost layer, which is where skin cancer first manifests itself. Basal and squamous cell carcinomas are also referred to as non-melanoma malignancies. Skin cancer that isn't melanoma always responds to therapy, and it seldom metastasizes to other skin tissues. The majority of other forms of skin cancer are less hazardous than melanoma. If it is not discovered in the early stages, it swiftly spreads to other regions of the body by invading surrounding tissues. Biopsy is a way for official diagnosis of skin cancer. A biopsy is a procedure to take a sample of tissue or cells from a patient's body so that it may be examined in a lab. This approach is awkward. Because testing requires a lot of time, the biopsy method is time-consuming for both the patient and the physician. Skin tissues (skin cells) are removed during a biopsy, and the sample is then subjected to a number of laboratory tests . The chance of a disease spreading to another bodily component exists. It is more dangerous. It is suggested to use svm for skin cancer screening in light of all the aforementioned circumstances. SVM is used in this methodology for classification together with digital image processing techniques.

## II. Objective

The objective of skin cancer detection approach is to classify the cancer images into either malignant or benign melanoma using convolutional neural network. Skin cancer is an alerting issue and it must be detected as early as possible. The diagnostic is a manual process that is time consuming as well as expensive. But, today's world science has become advanced by using machine learning and it can be helpful in many ways. Hence, machine learning can make easy for detecting cancerous cells and that is why machine learning specially convolutional neural network is used to detect cancerous cell more quickly and efficiently.

## III. Background and Scope

The most prevalent kind of cancer among people is skin cancer. Skin cancer may come in two primary forms: melanoma and non-melanoma. Since non-melanoma is typically curable through surgery and non-lethal, it is of less concern. Although it accounts for less than 5% of cases of skin cancer, melanoma is the most lethal type and has a high mortality rate. Worldwide melanoma cases are estimated at 132,000 per year by the World Health Organisation (WHO). Skin self-examination and skin clinical examination (screening) are traditional ways to find skin cancer early. Self-examination of the skin, in which the patient or a family member discovers a lesion, is a random procedure, nevertheless, because individuals may overreact or underreact. A dermoscope, microspectroscopy, and laser-based instruments are just a few examples of the pricy, specialised medical equipment that takes training, effort to use, time, and routine follow-ups in order to conduct clinical examinations. In order to obtain quicker diagnosis, individuals have begun adopting mobile technology like cellphones to communicate photographs with their physicians. However, online image sharing could jeopardise privacy. Even worse, inadequate image quality might result in incorrect diagnosis.The project's main goal is to employ AI as a tool to aid in the detection of skin cancer. Deep AI and shallow AI are both used in skin cancer diagnosis tools. Both entail modifying computer algorithms to learn from data created by specified characteristics through a process called training. The distinction is that shallow approaches frequently employ multilayer neural networks with a minimum number of layers, if at all. The training of huge, deep, multi-layer neural networks with several hidden layers, often numbering in the dozens to hundreds, is the approach used in deep methods.

## IV. Literature Survey

### *A. Automatic Skin Cancer Detection in Dermoscopy Images Based on Ensemble Lightweight Deep Learning*

In this paper, we proposed a lightweight skin cancer recognition model with feature discrimination based on fine-grained classification principle. The propose model includes two common feature extraction modules of lesion classification network and a feature discrimination network. Firstly, two sets of training samples (positive and negative sample pairs) are input into the feature extraction module (Lightweight CNN) of the recognition model. Then, two sets of feature vectors output from the feature extraction module are used to train the two classification networks and feature discrimination networks of the recognition model at the same time, and the model fusion strategy is applied to further improve the performance of the model, the proposed recognition method can extract more discriminative lesion features and improve the recognition performance of the model in a small amount of model parameters. In addition, based on the feature extraction module of the proposed recognition model, U-Net architecture, and migration training strategy, we build a lightweight semantic segmentation model of lesion area of dermoscopy image, which can achieve high precision lesion area segmentation end-to-end without complicated image pre-processing operation. The performance of our approach was appraised through widespread experiments comparative and feature visualization analysis, the outcome indicates that the proposed method has better performance than the start-of-the-art deep learning-based approach on the ISBI 2016 skin lesion analysis towards melanoma detection challenge dataset

### *B. Determination of border irregularity in dermoscopic color images of pigmented skin lesions*

Malignant melanoma, which is the most dangerous type of skin cancer, is commonly diagnosed in all people, regardless of age, gender, or race. In the last several years an increasing melanoma incidence and mortality rate has been observed worldwide. In this research we present a new approach to the detection and classification of border irregularity, one of the major parameter in a widely used diagnostic algorithm ABCD rule of dermoscopy. Accurate assessment of irregular borders is clinically important due to a significantly different occurrence in benign and malignant skin lesions. In this paper we describe a complex algorithm containing following steps: image enhancement, lesion segmentation, border irregularity detection as well as classification.

### *C. An Advanced image-Processing Mobile Application for Monitoring Skin Cancer*

This paper describes a mobile hardware/software system (DERMA/care) to help with screening of skin cancer (melanomas). Our system uses an affordable apparatus (microscope) and a smart phone (iPhone). These two components standalone are sufficient to capture highly detailed images for use by experts with medical background. However the novelty of our system lies in the fact that we further improved the efficiency of the system by implementing an advanced image-processing framework to detect suspicious areas and help with skin cancer prevention. Our main goal was to demonstrate how smart phones could turn into powerful and intelligent machines and help large populations without expertise in low-resource settings.

## V. Proposed System

Artificial Neural Networks are made of artificial neurons inspired by biological neurons present in our brain. Convolutional Neural Network (CNN) is a modified variant of feed-forward neural network which is generally used for image classification tasks. CNNs can recognize a particular object even when it appears in different ways, as it understands translation in variance. This is a key point which makes CNN advantageous over feed-forward neural networks which cannot understand translation invariance. In layman words, feed-forward neural networks only recognize an object when it is right in the center of the image, but fails notably when the object is slightly off position or placed else where in the image. The goal is to train a model to classify skin lesions as either benign (non-cancerous) or malignant (cancerous). The dataset used in the project is the ISIC (International Skin Imaging Collaboration) Archive. The data typically consists of images of skin lesions with corresponding ground truth labels indicating whether the lesion is benign or malignant. The training process involves using a large number of these images to train the model to learn the visual features that are indicative of a skin cancer. The network is trained to learn the underlying patterns in the images, such as color, texture, and shape. Once the model is trained, it can be used to classify new, unseen images of skin lesions, providing a quick and efficient way to identify potentially cancerous skin lesions, the figure 1. shows the architecture diagram of the proposed system.

### *A. Module Description*

*1) Input Image:* The resolution of the input image used here is 256*256.

*2) Pre-processing Module:* The following pre-processing on our training and test datasets:

a. Scaling and Normalization

The scaling across the channels is performed to prevent any form of training bias brought on by the direct usage of huge data from any of the six channels. This applied a min-max normalisation function from the Python Sklearn module to transform all of the channel values to a range between 0 and 1. However, because the scaling and normalisation stage takes care of the amplitude variation, the model is adaptive to moderate amounts of displacements. The algorithm can deal with any change in orientation due to the processing of raw time series from each channel.

b. Segmentation

After scaling the raw data, the six-channel input time series is divided into 1x128 windows so that any temporal relationship between the data inside an activity could be explored by the convolutional filters. The decision about the ideal window size

was determined in an empirical and adaptive way to create effective segmentation for all the activities taken into account.
c. Class relabeling and One-Hot encoding
The output activity labels are converted to One-Hot encoded labels. The activity windows are encoded to five unique labels.

*3) Gray Scale Conversion:* Gray scale image contains only brightness information. Each pixel value in gray scale image corresponds to an amount or quantity of light. The brightness graduation can be differentiated in gray scale image. Gray scale image measures only light intensity. 8 bit image will have brightness variation from 0 to 255 where '0' represents black and '255' represents white. In gray scale conversion color image is converted into gray scale image. Gray scale images are easier and faster to process than coloured images. All image processing technique are applied on gray scale image. In our proposed system coloured or RBG image is converted into gray scale image by using weighted sum method by using following equations Gray scale intensity= 0.299 R + 0.587 G + 0.114 B

*4) Noise Removal:* The objective of noise removal is to detect and removed unwanted noise from digital image. The difficulty is in deciding which features of an image are real and which are caused by noise. Noise is random variations in pixel values. In our proposed system we are using median filter to remove unwanted noise. Median filter is nonlinear filter, it leaves edges invariant. Median filter is implemented by sliding window of odd length. Each sample value is sorted by magnitude, the centermost value is median of sample within the window, is a filter output. In median filtering,first define the neighborhood.It is a set of pixels that surround the target pixel. The size of the neighborhood is defined by the filter window size.Then compute the median.Here the median of the values of the pixels in the neighborhood is computed.Then,replace the target pixel.The value of the target pixel is replaced with the median value.Repeat the process for each pixel in the image. Median filtering is a non-linear technique, which means that it preserves the edges and structures in the image while removing the noise. This is because the median value of a set of pixels is less sensitive to outliers (noise) than the mean value. As a result, median filtering is often used to remove impulse noise (salt-and-pepper noise) from images. One of the advantages of median filtering is that it is fast and easy to implement. However, it can also introduce blurring in the image, as it smooths out the edges and structures. This is because the median value is computed based on the entire neighborhood, rather than just the target pixel. To minimize this effect, it is important to choose a neighborhood size that is appropriate for the size of the noise in the image.

*5) Image Enhancement:* The objective of image enhancement is to process an image to increase visibility of feature of interest. Here contrast enhancement is used to get better quality result.Image enhancement for skin cancer detection using Convolutional Neural Networks (CNNs) is a crucial step in the preprocessing of images to improve the performance of the model. Image enhancement techniques are used to make the features of the skin lesion more prominent and to reduce the noise and background clutter in the images.

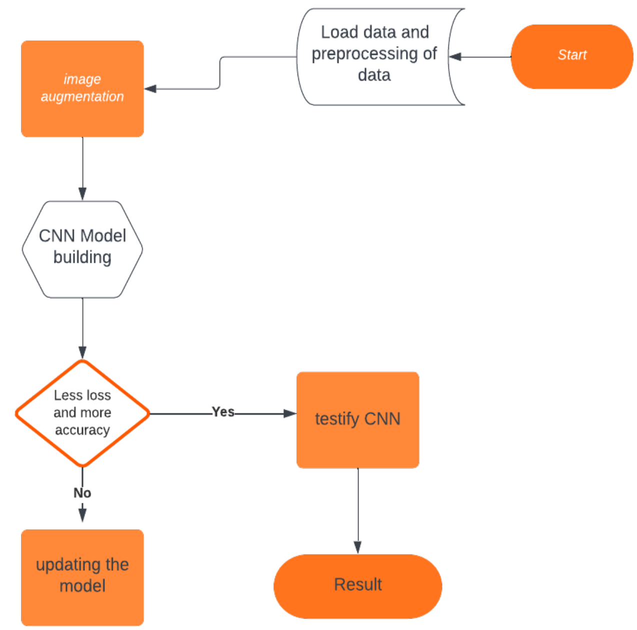


Fig. 1. Proposed System

## VI. Conclusion

In this research, skin cancer detection system using image processing is proposed and it is an improved diagnosis approach than the traditional Biopsy method. The computer technology based detection of skin cancer is more beneficial to patients. In this, the patients can ascertain the skin cancer in a very effective and accurate way while saving their time and prepares them for the treatment. In this project, the diagnosing method uses an image processing methodology. The project is conducted with the aim of developing convolutional neural network model to diagnose and detect skin cancer from lesion images. It also explored the data augmentation technique as a pre-processing step to strengthen the classification robustness of the CNN model.

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