Skin Cancer (Malign Moles) Detection Using Deep Learning

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SKIN CANCER (MALIGN MOLES) DETECTION USING DEEP LEARNING

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report "SKIN CANCER (MALIGN MOLES) DETECTION USING DEEP LEARNING" is the bonafide work of "HARSHIT BAJPAI, MD SOHARAB ANSARI, JAGMOHAN YADAV, ABHISHEK SHUKLA" who carried out the project work under my supervision.

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Abstract

Melanoma, most threatening type of skin cancer, is on the rise. In this paper, an implementation of a deep learning system on a computer server, equipped with graphic processing unit (GPU), is proposed for detection of melanoma lesions. Clinical (non-dermoscopic) images are used in the proposed system, which could assist a dermatologist in early diagnosis of this type of skin cancer. In the proposed system, input clinical images, which could contain illumination and noise effects, are preprocessed in order to reduce such artifacts. Afterward, the enhanced images are fed to a pre-trained convolutional neural network (CNN) which is a member of deep learning models. The CNN classifier, which is trained by large number of training samples, distinguishes between melanoma and benign cases. Experimental results show that the proposed method is superior in terms of diagnostic accuracy in comparison with the state-of-the-art methods. The image features used in the experiments were colour, shape, size and texture. Basically we selected images containing foods which are ready to eat. Then we applied Convolutional neural network, a feature detection and classification technique to extract these features of skin cancer (melanoma). We then spilt our dataset in 80-20 ratio as training and testing data respectively and trained our model.

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Chapter1: Introduction

Melanoma, also known as malignant melanoma, is a type of cancer that form the pigment-containing cells known as melanocytes. Melanomas typically occur in the skin, but may rarely occur in the mouth, intestines, or eye. In women, they most commonly occur on the legs, while in men they are most common on back. Sometimes they develop from a mole with concerning changes including an increase in size, irregular edges, change in color, itchiness, or skin breakdown. Despite significant death rate, early stage detected melanoma is curable in most cases. Meanwhile differentiation between melanoma and other benign moles in their initial growth phases is a challenging task even for experienced dermatologists. Computerized algorithms are being developed for this purpose. Some low complexity methods are designed, which are intended for running on tablets and smartphones, and can help non-specialists. But professional decision making, in this regard, requires sophisticated algorithms and equipment. There are various methods in dermatology such as ABCD (asymmetry, border irregularity, color patterns, and diameter) rule and the seven-point checklist that guide physicians in this task.

Deep learning approaches have shown promising results in some applications such as natural language processing, speech recognition and recently in computer vision areas such as object tracking, object detection, and image classification. Deep learning mechanisms can learn set of high level features from low level ones and gain high accuracy for classification applications without the need for extracting handcrafted features. Especially there has been a trend for taking advantage of superior power of deep learning methods in medical imaging tasks. Convolutional neural network (CNN) is a type of deep learning method where trainable filters and pooling operations are applied on the raw input images, extracting set of complex high level features automatically. The accuracy using

CNN is approximately 90.12%. The results are encouraging and promise a good computer vision system in the area of skin cancer (malign moles) detection.

Some Examples of melanoma are as follows : -

Fig.1 DERMIS MELANOMA

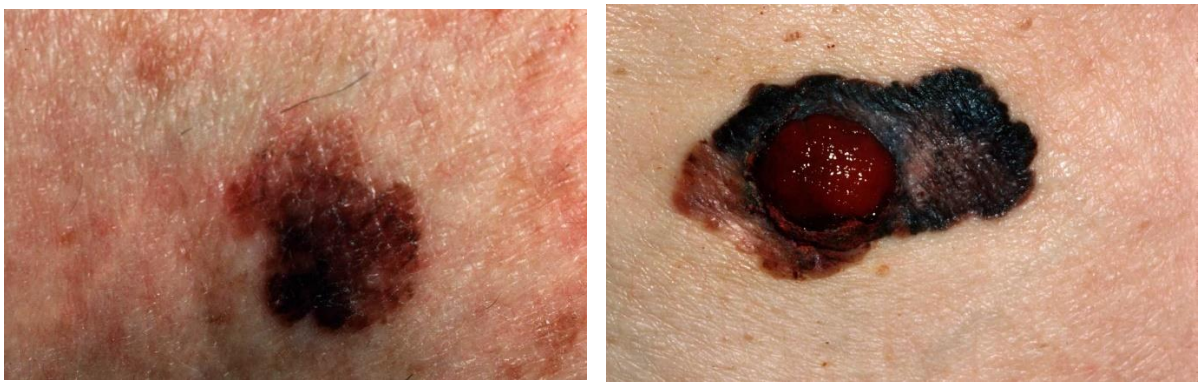

Fig.2 DERMQUEST MELANOMA

1.1 Motivation

The purpose of this project is to create a tool that considering the image of a mole, can calculate the probability that a mole can be malign. Skin cancer is a common disease that affect a big amount of peoples. Every year there are more new cases of skin cancer than the combined incidence of cancers of the breast, prostate, lung and colon. Skin cancer (malign moles) detection can be very useful for common people. These problems motivated us to implement our project.

1.2 Problem Statement

There are many types of skin cancer. Therefore it is difficult to recognise a particular type of skin cancer. It is tough task to collect images of the melanoma because all skin cancer look alike. So collecting datasets of melanoma (skin cancer) was a challenging task. Every image had different size than other. To improve accuracy, we had to resize each image to a particular size. To achieve better accuracy we need to set up many parameter in algorithms like images size which are processed, feature extractor (filter) size, no of feature extractor, no of layers in convolutional neural network etc.

1.3 Contribution of work

We realize image recognition of skin cancer (melanoma) with high accuracy by introducing convolutional neural network, a feature extraction technique. First of all, we build a 2-category food image set which includes 4 subclasses by gathering melanoma images from the Web and selecting1000 relevant images by hand for each subclass, since images on the Web are taken by many people in various real situations, which is completely different from an artificial

setting for experiments. Basically we selected images containing skin cancer (melanoma) which is at beginning . Then we applied convolutional neural network, a classification technique to classify melanoma or not melanoma. We then spilt our dataset in 80-20 ratio as training and testing data respectively and trained our model with CNN. It was observed through the results that accuracy now were much better through CNN architecture method.

1.3 Organization of report

The report is organized as follows:

Chapter 1 gives a detailed introduction about this project, our motivation behind this project and also describes the work which we have done in this project.

Chapter 2 describes the literature review of this project and also tells about the application of this project.

Chapter 3 describes the algorithm used in this project, techniques which were used to implement this project and also shows the flowchart which gives a brief understanding about the project.

Chapter 4 gives the implementation details like the language used, the processor used and also describes the type of images our dataset is composed of.

Chapter 5 discusses about the experimental results obtained over several image categories and also gives the accuracy obtained.

Chapter 2: Literature Review

2.1 Related work

Amelard *et al.* proposed a set of high level features that intuitively describes ABCD characteristics. Giotis *et al.* proposed a computer aided system that performs some preprocessing for enhancing the quality of the image. Then, some color and texture features of lesions are extracted automatically. Afterward, a set of attributes are provided by the examining physician and the final diagnosis is made by voting among observed and automatically extracted descriptors.
Automated analysis of pigmented lesions is a growing research topic that aims to develop tools for computer aided diagnosis of skin cancer [1]. Reviews of researches done in this field are given in [1] and [2].

Deep learning algorithm does as well as dermatologists in identifying skin cancer
BY TAYLOR KUBOTA

It’s scary enough making a doctor’s appointment to see if a strange mole could be cancerous. Imagine, then, that you were in that situation while also living far away from the nearest doctor, unable to take time off work and unsure you had the money to cover the cost of the visit. In a scenario like this, an option to receive a diagnosis through your smartphone could be lifesaving.

Researchers turn to AI and machine learning to help in early skin cancer detection**.** The skin we're in is the only skin we've got. With skin cancer ranking at the top of the most commonly diagnosed type of cancer, detection solutions are highly sought after in the medical field. Now researchers and scientists are turning to Artificial intelligence (AI) and machine learning to help. This technology has already shown promise in early detection in Alzheimer's and breast cancer.

2.2 Applications

This project finds great application in the medical field, in medical field as it can easily detect the skin cancer which a paitent has and diagnose it with the help of any doctors and doctors and patient can upload skin cancer images taken during diagnosis to the system from anywhere, and obtain a recognition result by a cellular-phone e-mail. As future work, we plan to return the full detail of that skin cancer and some medical advices on the skin cancer.

Chapter 3 :- Proposed Approach

In this section the proposed method is explained in details. The goal of this step is to reduce artifacts that could mislead the convolutional neural network. Preprocessed images are fed into second stage which is a CNN. Details of CNN are explained below.

3.1 Convolutional Neural Network

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 by using a large set of features we may feed some incoherent traits to the network. On the other hand, by using a small set of features there is a possibility of missing some proper descriptors. Hence, automatic feature extraction systems could be utilized to achieve a discriminative feature set based on labeled training set, without the need for definition of handcrafted feature extraction procedures. In this paper CNN, as a deep learning framework, is used for automatic detection of melanoma. CNNs take advantage of a set of powerful convolve-filters. They can examine various structures in input images. Hence, in utilization of CNN, the input is the image itself and the network automatically extracts appropriate aspects of the image.

Conventional CNNs usually contain several convolve and pooling layers and the last layer is made by a fully connected layer. Convolve layers filter the input image by a set of kernels. Usually each convolve layer is followed by a pooling layer. By selecting the maximum or mean values, in each defined window, the pooling layer reduces the size of the feature map. It is done for the purpose of recognizing some general patterns in the images. These general patterns are perceptible in resized image.

The used CNNs in this paper consist of two convolving layers with a 3 × 3 kernel. There are 32 feature maps in the first convolution layer and 32 feature maps in the second convolution layer. There is one pooling layer after each convolution layer. Outputs of these four layers are fed to a 2-layer fully connected stage respectively having 128 and 1 neurons. This 2-layer network forms the final diagnosis results with a linear transfer function. The proposed configuration can be seen in Fig. 3. The images of the dataset, after removal of noise and illumination artifacts, are fed to the proposed CNN.Usually there should be a large number of samples for proper training of any CNN. However, due to difficulties in collection and labeling of images the existinfigg datasets usually have limited number of images for detection of melanoma from non-dermoscopic images. Hence, we should cope with the limited training set. For this aim there are some approaches for automatic expansion of the trainingdata. For example an image is cropped from its top-left corner by cropping 5 percent from the top and from the left side of the image. Then, the new image is scaled back to the original size. This cropping method could be also done from three other corners. The same thing could be done with 10 percent cropping. This results in 8 images besides the original image. Afterward, these 9 images are rotated by 0, 90, 180 and 270 degrees. Therefore, 36 synthetized images are derived from each input image and the size of training set will be multiplied by 36. It should be noticed that all input images are resized to 188 × 188 pixels. The same approach is applied for the testing data, where 36 versions of each image are produced by cropping and rotation. The final diagnosis for any input image is made by voting among classification results of its 36 synthesized versions.

The network is trained through 30 iterations. To make the results independent from the selected training and test data, the procedure of learn and test is repeated 50 times and the mean values of different groups of results are reported. For quantitative evaluation of the performance of the proposed system, five

commonly used metrics in classification problems are measured. These metrics are defined as follow:

$$accuracy = \frac{\text{true detected melanoma cases}}{\text{all cases}}$$

For comparing the proposed method with other existing methods, three works that have reported their results on the same dataset are studied [12], [13] and [24]. Work of [24] is one of the early efforts in this field used as a baseline. Work of [13] is an example of existing commercial applications and method of [12] makes its final diagnosis in a semi supervised framework, where the opinion of a physician who has examined the lesion is involved. For the fairness of comparison, only the automatically extracted descriptors of the work of [12] are reported here. The evaluation results are shown in Table 1. As can be seen, the proposed method has the highest accuracy with respect to other state-of-the-art methods. These results show the effective power of utilizing a deep learning framework. However, some false classified images are shown in Fig. 3. In the left column are benign moles labeled as melanoma by our classifier and the right column are samples of missed melanoma cases.

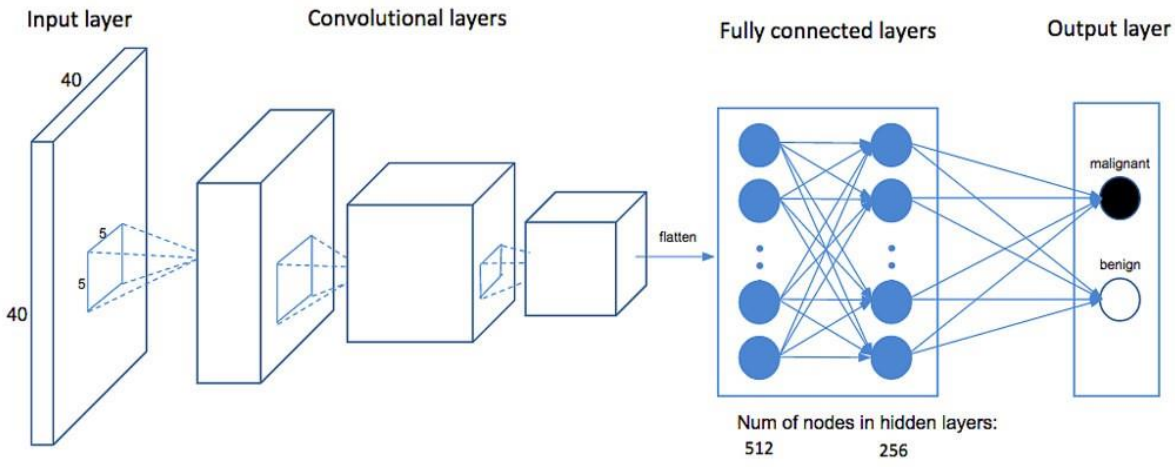

Fig.3 Convolutional Neural Network Architecture

Chapter 4 :- Implimentation

4.1 Language used:-

Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales.

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

4.2 Dataset :-

A number of images of skin cancer are required for the evaluation of skin cancer recognition. A melanoma image typically involves several classes. In the evaluation of melanoma recognition, each class region of the image need to be identified and isolated for the dataset.

We collected our dataset manually from different websites and refined them thoroughly. Then we make the resolution of every image into a single 188 X188 resolution. The dataset was then subdivided into training and testing with 80% - 20% ratio. Labelling was done for every image.

Dataset Classes

1. **Melanoma :-**

Dermis

Dermquest

S.No	Types of melanoma	No of images
1	Dermis	100
2	Dermquest	100

2. **Notmelanoma :-**

Dermis

Dermquest

S.No	Types of notmelanoma	No of image
1	Dermis	100
2	Dermquest	100

4.3 Machine used

Processor: Intel core i5

GPU: Nvidia GEFORCE

Memory: 8 GB

System Type: 64-bit Windows 10 Operating System

Processor

Perform Python Computations on CUDA GPUs

Using Python for GPU computing lets you accelerate your applications with GPUs more easily than by using C or FORTRAN. With the familiar Python language you can take advantage of the CUDA GPU computing technology without having to learn the intricacies of GPU architectures or low-level GPU computing libraries.

You can use GPUs with Python through Parallel Computing Toolbox, which supports:

CUDA-enabled NVIDIA GPUs with compute capability 2.0 or higher. For releases 14a and earlier, compute capability 1.3 is sufficient. In a future release, support for GPU devices of compute capability 2.x will be removed. At that time, a minimum compute capability of 3.0 will be required.

Chapter 5 :- Experimental Results:-

In the experiment, we carried out image classification for 2 different categories of melanoma images shown in above Figure to evaluate the proposed method.

First of all, we build a two category of melanoma which further have 2 subclasses, by gathering melanoma images from the Web and selecting 100 relevant images by hand for each category, since images on the Web are taken by many people in various real situations, which is completely different from an artificial setting for experiments. Basically we selected images containing melanoma which are at the beginning stage. For some images, we clipped out the regions where the target melanoma was located. Because originally our targets are melanoma, some unique melanoma images are included in the dataset, which might be unfamiliar with other people than Indian.

The image features used in the experiments were colour, shape, size and texture. Basically we selected images containing foods which are ready to eat. Then we applied Convolutional neural network, a feature detection and classification technique to extract these features of skin cancer (melanoma). We then spilt our dataset in 80-30 ratio as training and testing data respectively and trained our model.

Model use sigmoid function to predict the class which is as follows

Sigmoid function

$$\mathbf{A} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{x}}}$$

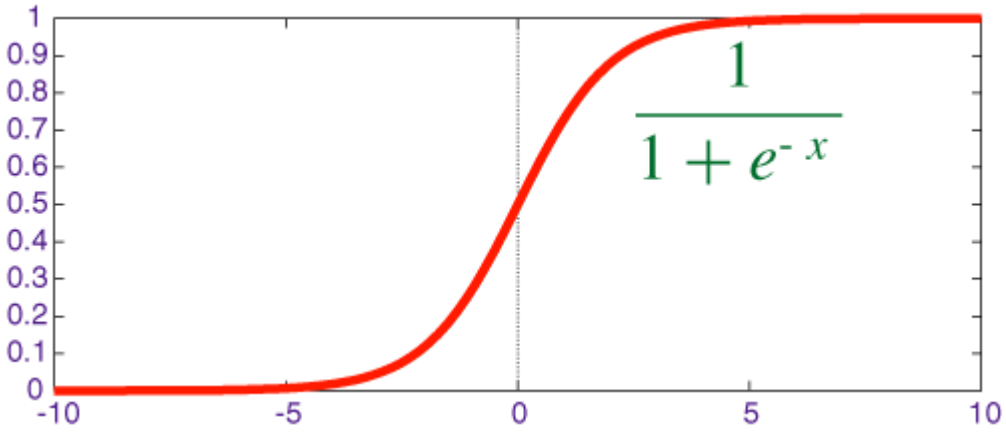

Fig.4 Sigmoid Function Graph

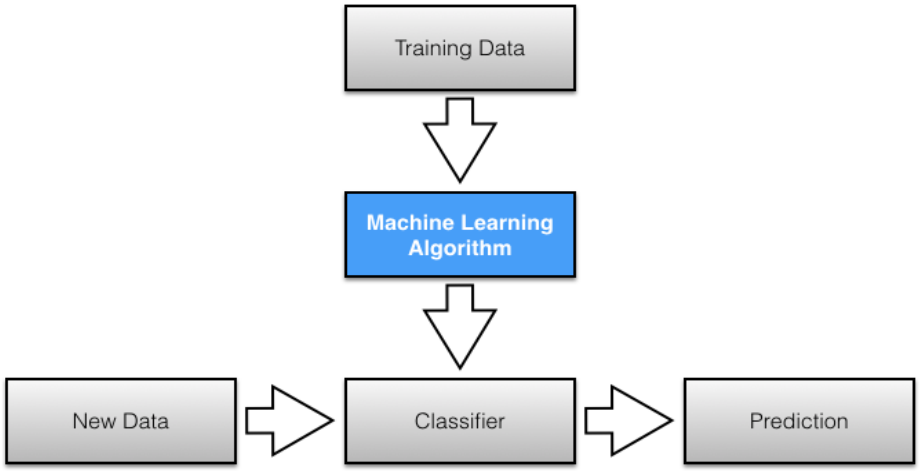

Fig.5 Block Diagram showing Proposed Approach

Algorithm	**CNN**
Accuracy	**80.5 %**

:- Accuracy Table

Confusion Matrix

The below figure shows Confusion matrices for CNN one of the traditional techniques. Bold letters show the class of high probability in which number above 0.700 gives correct accuracy and below it shows confusion probabilities increases.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	**0.722**	0	0	0	0	0.055	0	0	0.111	0	0.055	0	0	0	0	0	0.05	0
2	0	**0.666**	0.047	0	0	0	0	0	0.047	0	0	0.04	0.04	0	0.04	0	0.09	0
3	0	0	**0.761**	0.047	0	0	0	0	0	0	0	0	0.04	0.04	0.09	0	0	0
4	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	**0.904**	0	0	0	0	0	0	0	0	0	0.09	0	0	0
6	0	0.047	0	0	0	**0.809**	0	0	0.047	0	0	0	0.04	0	0	0	0.04	0
7	0	0.047	0	0	0	0	**0.904**	0	0	0	0	0	0	0	0	0	0	0.04
8	0.047	0	0	0	0	0	0	**0.333**	0	0.095	0	0	0	0.04	0	0.04	0	0
9	0	0.066	0	0.066	0	0.066	0	0	**0.666**	0	0	0.06	0	0	0	0	0.03	0.33
10	0	0.047	0	0	0	0.047	0	0	0	**0.857**	0	0	0	0	0	0	0.04	0
11	0.047	0	0	0	0	0.095	0	0	0.047	0	**0.761**	0	0	0	0	0	0.04	0
12	0	0	0	0	0	0	0	0	0	0.050	0	**0.95**	0	0	0	0	0	0
13	0	0.190	0	0.095	0	0	0	0	0	0	0	0	**0.67**	0.04	0	0	0	0
14	0	0	0	0.142	0	0	0	0	0	0.047	0	0	0	**071**	0	0	0.09	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0
16	0	0	0	0	0	0	0	0.045	0	0.045	0	0	0	0.09	0	**0.90**	0	0
17	0	0	0	0	0	0	0	0	0.047	0	0	0	0	0	0	0	**0.85**	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.04	0	0.09	**0.85**

Fig: 14 Confusion Matrix obtained using Convolutional Neural Network

Finally our proposed approach calculated accuracy of 80.562%.

Chapter 6: Conclusion and Future Work :-

In Skin Cancer (melanoma) detection and classification, there is a vast scope in which we can expand our project.

Some of them include:

- In future, we can expand our categories by including more and more Skin Cancer types in our project so as to make our idea more vast and how it can help for more and more people in determining the Skin Cancer.

- In future, we can expand the vision of computer to detect not only the Skin Cancer but also the vast types of the Skin Cancer all around the world.

- We can also implement image processing in our project so with some modification our project is use to analyse the stages of the skin cancer by taking images samples of different people and can predict the stage of the skin cancer by machine learning process.

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