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# *Melanoma Screening using Deep Neural Networks*

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***Abstract*—Deep learning algorithms, in particular convolutional neural networks, have rapidly become a methodology of choice for analyzing images.This choice arises due to fact that Deep Learning reduces the feature engineering task which is very important for automatic analysis of various kinds of images including medical images.In this work we have implemented various Deep Convolutional Neural Networks architectures for the process of binary classification task efficient enough in predicting either the input RGB image of the skin lesion is melanoma or not.Diagnosing the skin lesion is the first step towards its treatment.In this work we have assimilated two approaches on the pretrained Convolutional Neural Networks on the ImageNet dataset. Firstly, we use the transfer learning approach without any fine tuning and obtained features are fed for linear classification task. Secondly, we use the transfer learning approach with fine tuning. The adopted method requires no lesion segmentation or any other higher level image processing tasks.**
**Finally, we have also developed a real time android application to perform the binary classification task. The result obtained using our android application were enthusiastic.**

***Keywords*—Deep Learning , Transfer Learning, Fine Tuning , Melanoma Screening, ImageNet, Convolutional Neural Networks, Medical images, Machine Learning , Image Classification , Dermoscopy**

## I. Introduction

Skin Cancer is the most common form of cancer which occurs due to the development of abnormal cells. Skin cancer is of various types such as Actinic Keratoses , Basal cell carcinoma, squamous cell carcinoma and melanoma [1] . Commonly skin cancer lesions are grouped into melanoma and non-melanoma. Melanoma is the most dangerous form of skin cancer caused by unrestrained growth of melanocytes and has higher rate of mortality and on the other hand non-melanoma skin cancers have higher occurrence rate. Non-melanoma skin cancer occurs most commonly in people with light skin and it affects the quality of life of people [2] and on the other hand Advanced stages of melanoma can be extremely fatal thus early detection of melanoma is vital in reducing the number of deaths by increasing the odds for cure. Early diagnosis to separate melanoma, non-melanoma and other types of benign skin lesions is an important component of a practical skin diagnosis tool and constitutes the core of this work.

Various methods such as ABCD (Asymmetry, Border, Color and Diameter) scores[3][4], CASH algorithm and Menzies method are used by dermatologists for detection of melanoma but the accuracy of such diagnosis methods is highly subjective and is highly dependent on the experience of dermatologists [5]. Early detection of melanoma can be done with the help of Computer-Aided Diagnosis systems [6]. Since the accurate and fast diagnosis of skin lesion is not an easy task even for the dermatologists[7], a second opinion in diagnosis can help in increasing the accuracy of positive analysis. The advancement in the field of computer vision and computational power have helped in development of Computer-Aided Diagnosis systems that can provide a second opinion to the dermatologists in detection of melanoma in early stages.

There are numerous melanoma detection systems which use various pixel based features for melanoma detection which are derived in such a way that they can describe characteristics as an expert in melanoma detection[8],[9] have proposed features which can represent ABCD rule in melanoma detection. In[10] a system for performing some preprocessing for quality enhancement was proposed which is further used for extracting features of lesions to be used in melanoma detection task. K-nearest neighbor based approach was used in [11] to classify skin lesions images and similarly [12] classify images into four distinct classes.
Most of the research works in melanoma screening have skin lesion segmentation step where the region of skin lesion is separated from the overall image and this region of interest is used for further extraction of features and classification into melanoma and non-melanoma. Complex preprocessing such as removal of hair, shades and radiance are done before processing the image for melanoma detection.Our work is free from these complex preprocessing steps and hence saves time there.
Deep learning methods have been used in various applications in computer Vision such Object detection, object tracking and classification[13]. We have used Convolutional Neural Networks (CNNs) which automatically selects the most important features of the images to be used for classification and thus leads to more generic observation and transfer learning approach[14] has shown a verification in this property of Convolutional Neural Networks.

The organization of the remaining part of this work is as follows. Section 2 describes about the dataset used in this work followed by the description of main methodology which also includes relevant information about the CNN architecture used.Section 3 includes final results. Section 4 is about the android application developed by us which incorporates the research methodology, followed by conclusion in the section 5.

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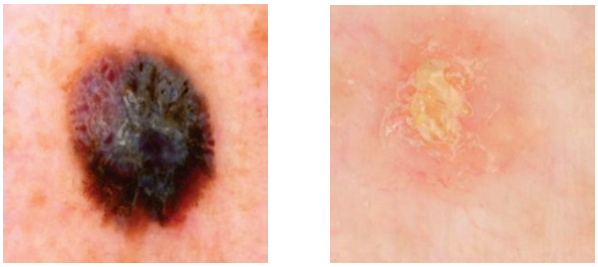
## II. Data And Methodology

### A. Dataset

International Skin Imaging Collaboration dataset (abbreviated as ISIC dataset) is one of the first openly available , public dataset. The first large scale challenge based upon ISIC dataset was introduced in the year 2016 [15]. It is an initiative led by International Society for Digital Imaging of the Skin (ISDIS).The second iteration of this challenge happened in the year 2017 [16]. Both the year this challenge was hosted at International Symposium on Biomedical Imaging (ISBI) in Czech Republic and Australia respectively. This challenge is organized with the aim of developing automated image analysis tool/mechanism for the diagnosis of the skin lesions.The challenge is divided in three parts :-

1) Lesion Segmentation
2) Detection and Localization of Visual Dermoscopic Features/Patterns
3) Disease Classification



(a) Melanoma (b) Non-Melanoma

Fig. 1: Melanoma and Non-Melanoma Lesion

In our analysis we took dataset from the 3rd part of the challenge , the dataset we took was the mix of both the year(year 2016 and 2017).We utilized the dataset as the binary data and divided it further in training and testing splits.In Fig.1 sample image from the dataset , definitely it can be noticed that the melanoma and no-melanoma images have different structure,colour and boundary distribution. The images present in the dataset were composed of all the three channels (RGB) and majority of them were 512 pixels in the height and 768 pixels in the width. The aspect ratio of the lesion was not fixed, as some of the images had skin lesion in the centre of them while others having a zoomed out shot of skin lesion. The original dataset was divided into multiclass problem as it was divided into subtypes of Melanoma,Non-melanoma and remaining being classified as Miscellaneous, but we took it as a binary classification scenario.
Apart from the ground truth the dataset was also supported with some various metrics such as how difficult is to classify the image manually by a trained dermatologist etc.Initially,on combining we were left with 2900 images in the training dataset and 979 images in the testing dataset. We brought this number to different ratio to satisfy our analysis and created training, testing and validation split out of the entire dataset.The entire dataset was in jpeg format.
During the training and development of pipeline part for generating the final classifier we are using the transfer learning techniques in which the already trained (pre-trained) deep neural network on the ImageNet Large Scale Visual Recognition Challenge 2012 dataset was used. The IMAGENET dataset [17] contains one million training images divided into 1,000 categories. We did not used our own versions of trained deep neural nets on the IMAGENET dataset instead we used widely available pretrained versions of them.
We developed entire pipeline on the opensource technologies using Python as the prototyping language , Keras [18] with the Tensorflow [19] in the back-end.

### B. CNN Architectures Used

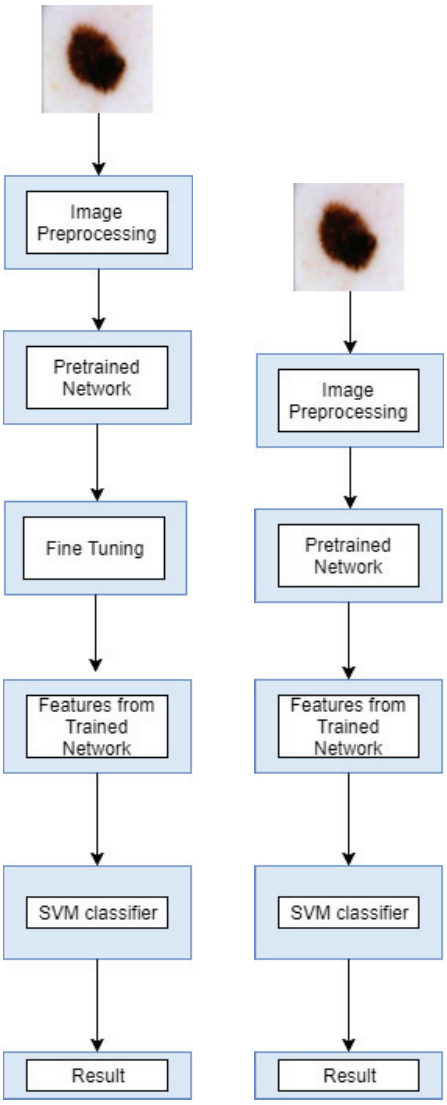
In this work we are using deep learning architectures famous for giving high accuracy for the classification of images. We have used VGG19 [20], ResNet50 [21] and Inception-V3 [22]. At the later stage, we have also used a Bucket of Models approach for the combined result of the above three architectures.We modified each architecture by removing the last two layers(softmax layers) from the state of the art architecture to use those features further in a binary SVM classifier.
VGG19 architecture has 19 layers on the whole.It has additional max-pooling and dropout layers in b/w.The size of kernel in the convolution filters in 3x3.Finally there are 241 million parameters in the end network.
The ResNet architecture is a very deep network. It consists of convolutional and pooling layers, along with the residual blocks in a repetitive way. Skipped connections are there to solve the vanishing gradients problem. There are 24 Million parameters in the final net.
Inception-V3 is a feature extractor designed at multiple levels.It computes 1x1 , 3x3 and 5x5 convolutions.The outputs of these filters are stacked together before being fed to the next layer.Inception-V3 is smaller in size than both the VGG19 and ResNet.

### C. Pipeline

In the beginning of the pipeline pre-processing of the image lesion is done.Standard pre-processing steps such as cropping and lesion centralization were used.On a larger level our classification pipeline can be divided into these exclusive steps :-

- Resize and central crop the images to 224X224 pixels.
- Load the pretrained Weights(trained on ImageNet) into the respective nets(VGG16 , Resnet50 and InceptionV3) and remove the softmax layer from each net.
- Insert the pre-processed training images batch-wise.
- In the case of Transfer learning - Freeze the pre-trained network and obtain the features directly from the last fully connected layer i.e. layer before the softmax layer(which is already removed).
  In the case of Fine Tuning - Unfreeze the pre-trained network and perform the iterations to let the model further adopt to our problem and obtain the features in the similar way like transfer learning.
- Store the features corresponding to each DNN to a different pickle file.

- Train the SVM classifier with the obtained features and evaluate the classification metrics on the test batch.
- For the combined classifier the Bucket of Models approach is used to get the final metrics.




(a) Fine Tuning (b) Transfer Learning

Fig. 2: Pipeline

## III. RESULTS

The results of classifiers corresponding to various networks and the combined classifier is as follows( shown in different tables). The True Class is ”Melanoma” and false class is ”Non-Melanoma”.

Results are obtained by evaluating each network on 979 test images. Tables I-IV show the number of True Positives, False Positives, True Negatives and False Negatives for Transfer Learning Technique and Fine Tuning Technique of each Architecture which we have used. In our case, True positives are the number of images of melanoma correctly classified as melanoma, False positives are the number of images which are not melanoma but classified by our system as melanoma, True negatives are the number of non-melanoma images correctly classified as non-melanoma and False Negatives are the number of melanoma images which are classified as non-melanoma by our system.

Table-V shows the comparison of all architectures based on the Accuracy obtained while using transfer learning and fine tuning. For better comparison of the architectures, True Positive Rate (TPR) of both transfer learning and fine tuning techniques of each architecture is evaluated. True Positive Rate is the ratio of correctly classified melanoma images to the total number of melanoma images in the test data(1).True Positive Rate Evaluation is essential measure in medical diagnosis since

| VGG-19 | | | | |
|---|---|---|---|---|
| **Technique** | **True Positives** | **False Positives** | **True Negatives** | **False Negatives** |
| Transfer Learning | 144 | 119 | 669 | 47 |
| Fine Tuning | 149 | 111 | 677 | 42 |

TABLE I: VGG-19 Results

| RESNET-50 | | | | |
|---|---|---|---|---|
| **Technique** | **True Positives** | **False Positives** | **True Negatives** | **False Negatives** |
| Transfer Learning | 139 | 126 | 662 | 52 |
| Fine Tuning | 145 | 116 | 672 | 46 |

TABLE II: RESNET-50 Results

| INCEPTION-V3 | | | | |
|---|---|---|---|---|
| **Technique** | **True Positives** | **False Positives** | **True Negatives** | **False Negatives** |
| Transfer Learning | 136 | 119 | 669 | 55 |
| Fine Tuning | 140 | 126 | 662 | 51 |

TABLE III: INCEPTION-V3 Results

| COMBINED | | | | |
|---|---|---|---|---|
| **Technique** | **True Positives** | **False Positives** | **True Negatives** | **False Negatives** |
| Transfer Learning | 144 | 114 | 674 | 47 |
| Fine Tuning | 150 | 109 | 679 | 41 |

TABLE IV: COMBINED

| Architecture List | | | | |
|---|---|---|---|---|
| **Architecture** | **Accuracy(TL)** | **Accuracy(FT)** | **True Positive Rate(TL)** | **True Positive Rate(FT)** |
| VGG-19 | 0.83 | 0.84 | 0.75 | 0.78 |
| RESNET-50 | 0.81 | 0.83 | 0.73 | 0.76 |
| INCEPTION-V3 | 0.82 | 0.82 | 0.71 | 0.73 |
| COMBINED | 0.84 | 0.85 | 0.75 | 0.79 |

TABLE V: COMPARISON TABLE, TL(Transfer Learning only), FT(with Fine Tuning)

incorrect melanoma diagnosis can be fatal for the patient.

$$TPR = \frac{TP}{P} = \frac{TP}{(TP + FN)} \quad (1)$$

where:

- $P$ = Total number of melanoma images in the test dataset
- $TP$ = True Positive i.e. Number of images of melanoma correctly classified as melanoma
- $FN$ = False Negative i.e. Number of melanoma images which are classified as non-melanoma

The analysis of results shows that all the networks have performed well considering the fact that the number of images available in the training set were less. The best performance is obtained by the combined architecture with best accuracy and true positive rates among all the architecture used in this study.

## IV. ANDROID APPLICATION

Since the results were encouraging , we thought to take this work a step ahead and implemented it on widely used android framework.We developed an android application using opensource tools and libraries to accumulate our entire result pipeline. This application can help the user to detect melanoma by uploading images of skin lesion using an efficient user interface.
Fig-3 and Fig-4 shows the output as generated by the android application.Fig-3 shows the classification of image as benign which is non-melanoma and Fig-4 shows the classification of image as melanoma.

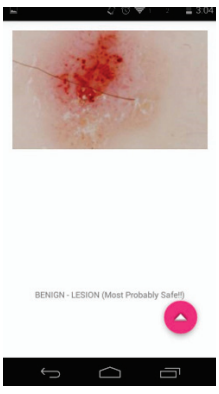



Fig. 3: Android Application detecting Benign Image.


Fig. 4: Android Application detecting Melanoma Image.

Fig.5 shows the complete flow of this process.

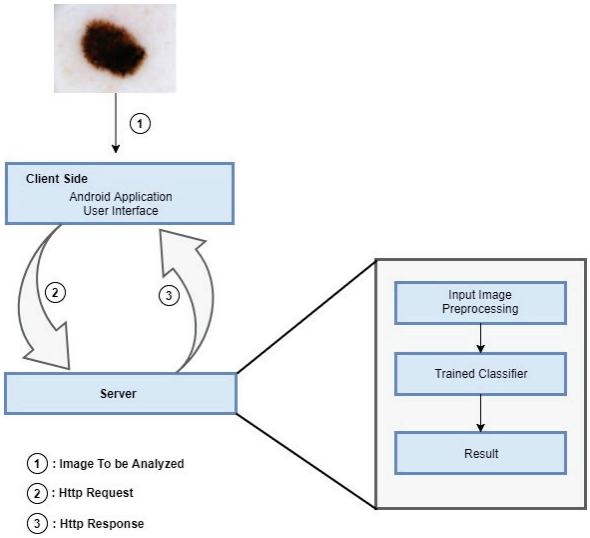



Fig. 5: Flow Chart Of the Android Application.

The entire pipeline from a larger perspective can be divided into these steps :-

- The uploaded image is sent to the server(using http protocol) hosting the trained model that helps in analyzing the image of skin and detect cancer.
- Once the uploaded image is received by the server, it is first prep-processed to be used as an input to the trained deep learning classifier.
- The class of the skin lesion as detected by the model is returned to the user's device as a http response and is displayed on the screen.

The whole process takes an average time of 15 seconds to generate the results.Several other applications also exists in this domain but very few of them adopt the deep learning techniques, larger proportion of them is based upon pixel based processing. For example most of the Applications analyze pictures of skin lesions using the ABCD (asymmetry, border,

color, diameter )[3] method undertaken by dermatologists. Some uses a mathematical theory called "fractal geometry" to analyze images of skin lesions and moles taken by the user.

## V. CONCLUSIONS AND FUTURE WORK

The results suggest that the experimental design is sensitive to the choice of lesions to compose the positive and negative classes, maybe due to the relative difficulty of identifying class.We were finally able to develop a classifier to predict the class of an unknown skin lesion image with significant accuracy(two class accuracy around 85 percentage). We propose an android application for the compact prediction of the same and for the wider reach to the audience.In the near future, we would further like to explore the various architecture of DNN in this scenario. The on-line processing time of a sample lesion on our Android Application can be scaled down to a significant factors if the faster and more efficient way of receiving the candidate lesion and pre-processing it can be embedded into the framework. Also, it would be intuitive to train the network on more different and significantly variant images, although the domain of Skin Cancer research is still restricted in this area due to less availability of open source, high quality data in optimum amounts.

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