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Comparison and Analysis of Skin Lesion on Pretrained Architectures

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Abstract - *Early stage detection of skin cancers is one of the most challenging as well as an expensive task. It is a strenuous job even for an experienced and a proficient dermatologist as there exists a minute incongruity between the lesion and the surrounding skin. Skin cancer is an abnormal growth of skin cells. It generally develops in areas that are exposed to the sun, but it can also form in places that don't normally get sun exposure. The project aims to perform analysis on the images of infected portions of the skin and can be further used to classify the skin cancer into a category. Various preprocessing techniques are applied on the image of skin cancer taken/uploaded for eliminating noise and managing image resolution from the image. The paper aims to use the dataset of HAM10000 for classification of skin cancer into 7 categories. Image processing and a deep learning model are parts of the diagnosing methodology. The paper shows a framework which incorporates transfer learning using various pre-trained models to obtain better results. The project uses a convolutional neural network to accurately detect and classify skin cancer. We have used several architectures such as MobileNet , ResNet50. EfficientNet B1 classifies skin lesion images with a validation accuracy of 94.1 percent, top3 accuracy of 99.0 percent and top5 accuracy of 99.9 percent. The weighted average of precision, recall, and f1-score were found to be 0.94, 0.94, and 0.94 respectively. The era of mobile technology opens up the windows for the android apps. The dominant use of mobile apps over conventional websites has encouraged the development of an android app for the same.*

Key Words: Skin Cancer, Transfer Learning, Computer Vision, Convolutional Neural Network, Image Classification

1. INTRODUCTION

Skin cancer is the most common cancer worldwide, with melanoma being the most deadly form. In the U.S., more than 9,500 people are diagnosed with skin cancer every day. More than two people die of the disease every hour[10]. Dermoscopy is a skin imaging method that has demonstrated improvement for diagnosis of skin cancer lesions compared to unaided visual inspection. Nowadays, skin cancer is steadily rising due to the exposure to the UV rays. Since skin cancer is becoming one of the major causes of deaths, so there is a need of the hour to find

an effective solution to detect them before they become incurable. If we can detect these types of skin cancers at an early stage then there is a higher probability to cure the cancer successfully.

Artificial Intelligence is the new electricity, evident from the events of the past 50 years. With the help of it, several medical related problems can be solved. Its application aims to scrutinize relationships between intercepting or medicating techniques and patient aftermath. Recent advancements have advocated the employment of Artificial Intelligence to outline and assess the aftermath of maxillo-facial surgery or the valuation of cleft palate therapy in concern to facial allure or age surfacing .The employment of Artificial Intelligence for the betterment of descrying precision of skin cancer can result in enhanced outcomes in contrast to that of dermatologists. On an average statistic, 86.6% and 95% are the descrying accuracy of skin cancers for the human dermatoligists and the CNN machine[11] respectively.In this paper, we are using several deep neural network models that analyze the skin lesion images and classify them into seven classes using a publicly available dataset. We have increased the validation accuracy of classification by implementing CNN with transfer learning models.

2. RELATED WORK

Image classification has been a hot topic since it came into existence and after that many researchers have been working on skin cancer detection and classification. The researchers and maestros have already employed a diverse number of techniques for the task of image processing to assist the categorization of skin lesions. For instance, the methods such as border and edge detection have been used for the bifurcation of skin lesion images. In [5], author hired an automated Global border detection technique meant for the dermoscopy images that is rooted on the color space analysis and global histogram thresholding depicting an enhanced execution in detection of the borders of melanoma lesions.

In recent years, Convolutional Neural Networks(CNN)[6] have outperformed other image processing tasks for object detection, segmentation and classification. The amalgamation of CNN models with the emerging techniques such as transfer learning[1] has eclipsed highly trained and proficient human experts in the mission of skin cancer classification. In [4], the author had used the ResNet50 model that yielded 90.51 % accuracy. Another author [12] uses dilated convolution for the skin lesions classification to obtain 89.81% with the help of MobileNet. In this paper, we have compared different pretrained models that analyse the skin lesion images and classify them into seven classes using a publicly available dataset. We are able to achieve the validation accuracy upto

94.1% by implementing EfficientNet B1 model as the base model for transfer learning.

3. DATASET

Finding a dataset is a huge problem for the challenges which are related to medical science and image classification. But nowadays there are so many platforms which provide free access to the large datasets. We are using SKIN CANCER MNIST: HAM10000[3] ("Human Against Machine with 10000 training images") which is provided by ISIC in 2018 .It consists of dermatoscopic images which are collected from different parts of populations, acquired and stored by different manner. The dataset includes lesions with multiple images, which can be accessed by the lesioned column within the HAM10000_metadata file. This has total 10015 images and consist of the seven different types of skin cancer images as depicted in Table 1.As we can see more than 50% images belongs to one particular cancer type i.e. Melanocytic nevi which makes this dataset a very imbalance in nature.

Table -1: Types of Skin Cancer

Cancer Type	Number of images
Melanocytic nevi	5954
Melanoma	1074
Benign keratosis	1024
Basal cell carcinoma	484
Actinic keratoses	301
Vascular lesions	131
Dermatofibroma	109
Total	10015

4. DATA PREPROCESSING

The training images in the dataset are often of different sizes and pixels, but the deep neural networks model requires fixed-size input images. The shape of the input images for the popular deep learning models are often square matrices, such as 224x224 for ResNet, MobileNet, Densenet model, EfficientNet B0, 256X256 for Inceptionv3 and 240x240 for Efficientnet B1[13] . We used Keras ImageDataGenerator[9] to wrap the lesion images to a fixed size. The input images are preprocessed with the help of preprocess_input function which is provided by the pretrained models. Dataset also consist of duplicate images , so we have splitted the data into train and validation datasets in such a way that the both sets are disjoint in nature. At last, to change intensity values of the pixels of every sample we normalized our data by dividing one and all pixel values of an image by 255 to rescale the range of 0-255 for each pixel values to 0-1 range.

5. DATA AUGMENTATION

The simplest augmentation method is to use some re-sampling schemes to enlarge the number of training samples. Normally, the skin lesion are located at the center of the dermoscopy images. But, due to the difference in the image condition and scaling , the skin lesion in the images can be present in different positions. The problem of imbalance in the training samples of the training set leads to an unwanted bias towards the dominant category. To overcome this, we only augmented all the classes except the Melanocytic nevi. We use several augmentation schemes, including scaling, horizontal and vertical flipping, rotation, height_shift and width_shift. Random cropping with scale and rotation adaptation. We also observed that the location of the skin lesion in the captured dermoscopy images have some differences from one image to another.

6. IMPLEMENTATION

We have used several state of the art Convolutional neural networks models as base models for our transfer learning which are pre trained on ImageNet[2], including densenet121, resnet50, mobilenet_v2, mobilenet, efficientnet b0 and inception_v3. These base models are pre-trained on imagenet dataset. We are using 83/17 train/val split on the constructed training dataset to do the cross-validation. The training procedure of our approach is described as follows. We modify the network definition by alternating the logits unit in the base network. Then all the

layers including lower convolution layers are fine tuned. We are using Adam[7] optimizer for this step with a start learning rate of 1e-2 for most of the models , but used 1e-3 for EfficientNet
.We perform 30-40 epochs for each model according to the requirements and update the weights with batch size from 32. All training codes are based on Keras and tensorflow framework[6], carried on one Nvidia Tesla P100 card. We have used several callbacks like ModelCheckpoint to save the best model for future use. The learning rate decreased by a factor of 0.1 by monitoring validation loss. To prevent models from over-fitting, we check the performance of the trained model after every 5 epochs and do early stopping.

But EfficientNetB0 and EfficientNetB1 outperforms all the previously used pretrained models on the HAM10000 and gives validation accuracy more than 90% and validation loss less than 25%. We have removed the last dense layer and replaced it with the three batch normalization and dropout layers and in last added a dense layer with softmax activation. Swish Activation is used in the last layers as activation function. Also we have unfreeze all the layers for training as the imagenet dataset is not similar to our dataset.

Table -2: Comparison of several combinations of pretrained models for training accuracy, validation accuracy, training loss, validation loss, precision, recall, f1-score.

S.No	Models	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	INCEPTIONV3	0.65	0.71	0.89	0.84
2	RESNET50	0.96	0.81	0.08	2.32

3	DENSENET121	0.87	0.77	0.31	1.60
4	MOBILENET V2	0.84	0.82	0.40	0.56
5	MOBILENET	0.84	0.78	0.39	0.73
6	EFFICIENTNET B0	0.94	0.93	0.14	0.21
7	EFFICIENTNET B1	0.95	0.94	0.12	0.20

Table -3: Comparison of several combinations of pretrained models for precision, recall, f1-score.

S.No	Models	Precision	Recall	F1-Score
1	INCEPTIONV3	0.66	0.58	0.61
2	RESNET50	0.73	0.81	0.74
3	DENSENET121	0.79	0.78	0.76
4	MOBILENET V2	0.80	0.83	0.79
5	MOBILENET	0.86	0.81	0.81
6	EFFICIENTNET B0	0.93	0.93	0.93
7	EFFICIENTNET B1	0.94	0.94	0.94

7. RESULT

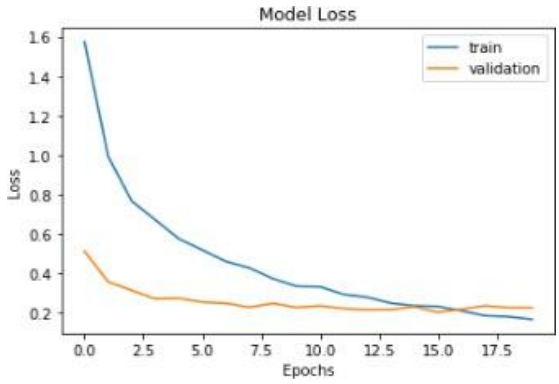


Fig -1: Implementation Graph: Model Loss

Now we will show Implementation Graph for Model Accuracy for the EfficientNet B1

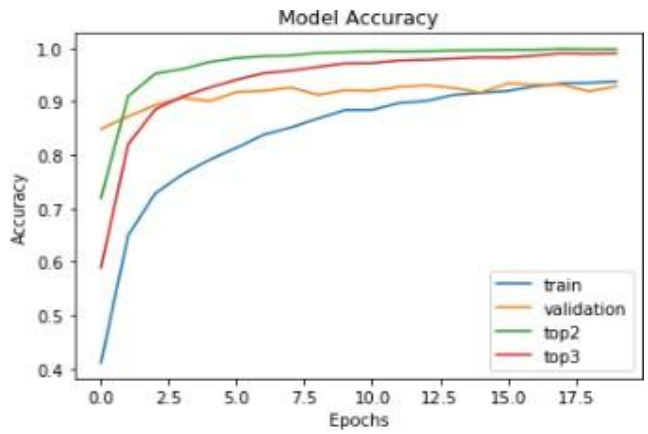
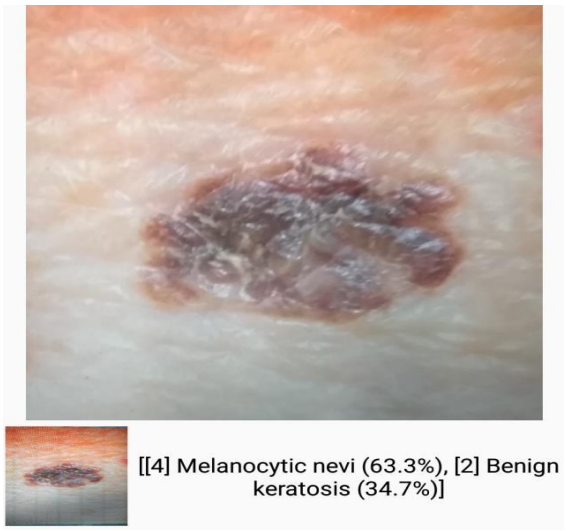


Fig-2: Model Accuracy for the EfficientNet B1

We have used categorical accuracy, top2 and top3 to calculate the accuracy and categorical cross- entropy for the calculation of loss. We have depicted the results for EfficientNet B1in the following figures .Figure 2(a) shows that how validation loss starts with 0.5 initially then decreases to 0.2. Figure 2(b) also shows how validation accuracy is close to the training accuracy which depicts that our model is perfect fit.

8. OUTPUT SCREENS

The output screens depict the probability of the different classes which can be present in the image which is clicked by the user. Figure 3(a) depicts image consist of 63.3% of Melanocytic nevi and 34.7% Benign keratosis. In figure 3(b) model classifies image into Melanocytic nevi with 99.9% probability.



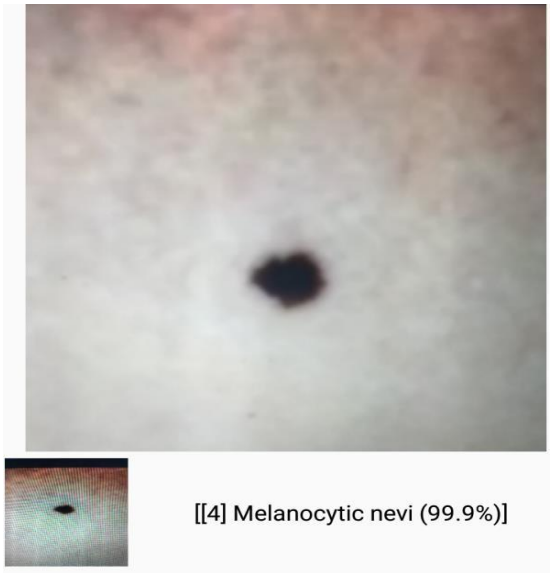


Fig-3: Output result (a) and (b)

9. CONCLUSION

The procedure nominated through this paper commence with the task of feature extraction which will assist in training of the learning model. After employing diverse kinds of learning models and techniques, we infer that the classification accuracy of skin cancer can be enhanced using Transfer Learning mechanism. In addition to this, we also converge to a point that the pre-trained Efficient Net B1 model is a substantial assist in the triumphant classification of the skin cancer. Further, it was discovered that learning models like ResNet50, Inception_V3 and DenseNet are less significant in the mission of classification in contrast to Efficient Net B1.We also saw that our model is biased towards mainly two classes due imbalance in the dataset. These outcomes stimulated us towards the refinement of prediction results and classification accuracy in our forthcoming work. New classes of cancer can also be appended for the task of classification by using a more balanced dataset comprising images of additional types of skin cancers.

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