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Skin Cancer Detection using Convolutional Neural Networks

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Abstract - *Skin cancer is the out-of-control development of unusual cells in the epidermis, the outermost skin layer, brought about by DNA harm that causes harmful variations. These changes lead the skin cells to duplicate quickly and form dangerous tumours. Despite consistent upgrades in medication, skin cancer is still an issue. According to the insights by the Skin Cancer Foundation, one of every five individuals will develop skin cancer by age seventy. The paper expects to plan a framework that will be adequately proficient to distinguish the occurrences of different sorts of skin malignancy in the body by extracting significant patterns from the dataset.*

Key Words: Skin Cancer, Convolutional Neural Networks, MobileNet, HAM10000, HealthCare, Sequential CNN, Skin Care

1.INTRODUCTION

Skin cancer is typically caused by unnecessary sun exposure or because of some toxic radiation. Melanoma is the fifth most common skin malignancy in the world. In twenty percent of the cases, even complex medical procedures like surgery and laser treatment fail to fix it. In overall skin disease related deaths, seventy-five percent of them occur because of melanoma. Knowledge about it, and identifying it in its early phases can help decrease the pace of its casualty worldwide and the number of instances of recently infected personnel [1]. The majority of customary systems out there perform just proper twofold (binary) classification. CNN produces a breathtaking exhibition in image classification problems, yet, the limit of the technique is that it is data-hungry and it isn't appropriate for small datasets. The traditional strategy that has been followed up until this point, by specialists, to identify melanomas in people is the ABCDE approach. It represents Asymmetry, Borders, Color, Diameter, and Evolving [9]. More unevenness or boundary anomalies is the main cautionary symptom, just as strange color of the scar and its size more than 6mm are some of the different alerts.

1.1 Literature Review

A five-layer CNN has been used for classifying three types of dermatoscopic ailments-melanoma, common nevus and atypical nevus. PH2 data set has been used, and it contains 200 images. Less no. of images is the limitation. Sometimes 100 percent testing accuracy has been noticed. So, dropouts were added while training the model, but the problem of overfitting was persistent [2]. Next implementation consists of the model which uses pre-trained Xception architecture with prior image segmentation. The upper classifying layers were frozen and new ones were added to classify diseases. The classification of malignant and benign tumours provided eighty-nine percent accuracy [4]. In the implementation of this paper, the images have been classified as benign and malignant, and it consists of 2437 training images, 660 test images and 200 validation images. The model has been implemented using Resnet-101 and Inception-v3 architecture. Resnet has an accuracy of 84.09 percent, also train and loss lines are almost constant after fifty epochs and the training accuracy reaches a saturation point after the fiftieth epoch. Inception-v3 has an accuracy of 87.42 percent. Here train and validation accuracy start varying drastically after the fortieth epoch [3]. Next, the authors have proposed their research on MobileNets based on depth wise separable convolutions. The research includes comparison between various MobileNet models and other models and proves how the MobileNet model is better with respect to size, speed and accuracy. They've also given a method to build short and quick MobileNets by implementing width and resolution multipliers by compromising a small amount of precision to decrease the size and latency [8].

1.2 Dataset

The HAM10000 dataset contains 10,015 images of seven different types of benign and malignant scars, and their abbreviations are labels. The seven types are Melanocytic Nevi, Melanoma, Benign Keratosis-like Lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesions, and Dermatofibroma. Checking the number of images present for each labelled disease has been done. [7]. Maximum number of images are of Melanocytic Nevi, and Dermatofibroma has the least number of images, so class imbalance is prevalent. According to the research done for this paper, only Melanoma, Basal Cell Carcinoma are malignant scars and they should be treated without any delay. Whereas Melanocytic Nevi and Actinic Keratosis may/may not become carcinogenic over a period of time, though a close watch should be kept at them. Benign Keratosis, Vascular

Lesions, and Dermatofibroma are completely harmless and they can be treated by medications.

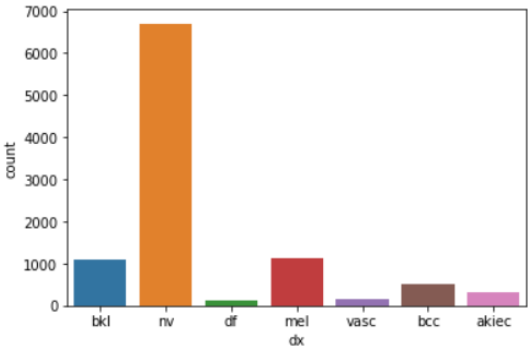

Fig - 1: Counting the no. of images in each class

2. RESEARCH METHODOLOGY

2.1 Implementation of CNN Model:

First of all, importing all the python libraries required for exploratory data analysis and establishment of CNN model has been done. Then, the next step is getting all the parameters because of which images are labelled is done by reading the metadata file. Then, checking the number of images present for each labelled disease has been done. After finding the mean of ages and replacing that mean value in place of NaN values, further inconsistency can be avoided. Images are in RGB format with most of the dimensions as (450,600,3). Resizing images to (90,120,3) has been done for ease in training. Now, after grouping the images, the next step is pre-processing.

For this, split the data into two parts with a test size value of 0.01. Hence, 9914 images are used for training and 101 are used for testing. After getting mean and standard deviation of both training and testing data, a binary matrix representation of the training and testing data is done. Now, the next step is to split the training data of 9914 images into two parts i.e., training data and validation data, and assigning the test size value as 0.15. Now there are three categories of data: train, test and validation, each having 8426, 101 and 1488 images respectively. Next step is model building.

Utilization of the Keras Sequential Model has been done, where one layer is added at a time, beginning from the input. The first is the Conv2D layer, a bunch of learnable filters. Set thirty-two channels for the first two Conv2D layers and sixty-four channels for the last two ones. Each channel changes a part of the image (characterized by the kernel size) utilizing the kernel filter, and the filter is applied on the whole image. CNN can extract features that are valuable from these transformed images. The second significant layer in CNN is the pooling (MaxPool2D) layer. It takes a look at the two adjoining pixels and picks the maximum value. These are utilized to decrease computational expense, and additionally, also reduces overfitting. Choosing a large pooling size is necessary. The pooling dimensions and down sampling are directly proportional to each other. After combining Conv2D and MaxPool2D layers, CNN can combine already visible nearby features and learn more about some other features of the image which are not that common. Dropout is a tool for regularization, where the weights of the nodes in the layer are set to zero per training sample. Thus, the features are learnt in a distributed way by the network. This is used for generalizing the network and to reduce overfitting. A rectifier named 'relu' (activation function max (0, x)) has also been used to avoid linearity in the model. The Flatten layer is used to convert the last feature maps into a single 1D vector. It combines every one of the obtained features of the past layers. After utilizing the features in the Dense layers, in the last layer, the net outputs the probability of each of the types.

Then, there is a need to compile the model. Compiling the model takes three parameters: optimizer, loss and metrics. The optimizer controls the learning rate. In this paper, utilization of 'adam' as the optimizer has been done, which is a decent optimizer for many use cases. The Adam optimizer changes the learning rate throughout training. The learning rate decides how quick the ideal weights for the model are determined. A more modest learning rate may prompt more exact weights up to a certain point, however the time it takes to compute the weights will be longer. Also, 'categorical_crossentropy' is utilized for the loss function. This is the most well-known decision for classification. A lower score shows that the model is performing better. To make things simpler to decipher, the accuracy metric has been used to see the precision score on the validation set when the model is trained.

Next, the fit () function has been used on a model with the given parameters: training data, target data, validation data, and the number of epochs. The number of epochs is the number of times the model will cycle through the data. More the epochs, the more the model will improve, up to a certain point. After that point, the model will quit improving during every epoch.

2.2 Implementation of MobileNet Model:

Recent work has shown that CNNs can be more efficient, easier to train and more accurate if the connections between layers near inputs and outputs are shorter. MobileNet is a deep neural network dependent on modifications of the connections between layers. In the traditional networks, one layer is associated uniquely to the following one, while MobileNet utilizes depth wise separable

convolutions which map a solitary convolution on each input channel independently.

In this paper, selection of this model has been done because of its lightweight neural network architecture and its compatibility with all applications. The dataset as mentioned before is HAM10000. The dataset has seven features with their names, i.e., lesion_id, image_id, dx, dx_type, age, sex, localization. The lesion_id is an ID that portrays the patient's identity while image_id is a numbering ID that describes an image [3]. This dataset has been isolated into training data, and validation data. Train set consists of 9077 images and the validation set consists of 938 images. Absence of duplicate images in the validation data has been ensured. Seven folders of each class have been made for this dataset, inside both training and validation folders.

By the data augmentation process, the quantity of data to be handled is increased. In this way, the quantity of data belonging to all classes is adjusted, almost equally. The new data is created by changing spatial properties of the pictures by flipping, rotating, by changing intensity of light in the images, and by zooming the images. Augmentation of the images of all classes has been done except Melanocytic Nevi (because of its already existing large quantity of images). After augmentation, training data comprises 38569 images.

In the next stage, pre-processing is done to the training data and validation data. The initial phase in pre-processing information is to resize the image. This pre-processing is done using Keras Image Data Generator. The dataset images have been downscaled to 224*224-pixel resolution for ensuring compatibility with the MobileNet model.

Now, load the MobileNet model from Keras. Exclude the last five layers of the MobileNet model. This will incorporate all layers up to and including global_average_pooling2d_1. Then another dense layer for predictions for seven classes is made. The last twenty-three layers of the model will be considered for the training process, after freezing all the weights of the other layers. Then, after defining Top2 and Top3 Accuracy, add loads to different classes as 1.0 and 3.0 for (mel) to make the model more sensitive to Melanoma on account of its close similarity to Melanocytic Nevi. After obtaining the required results, conversion of the model into a .json file using TensorFlowJs has been done. TensorFlowJs is a library that permits machine learning models to run on the browser, without downloading or installing any additional software, and the outputs are acquired. Here, in this paper, three most probabilistic outcomes have been shown.

3. RESULTS AND DISCUSSIONS

Sequential CNN:

For this model, epochs have been set to 15, since this is only for reference purposes. After 15 epochs, 75.47% as the maximum accuracy on the validation set has been obtained. Plotting of graphs for training accuracy vs. validation accuracy, as well as for training loss vs. validation loss has been done. The results are as follows:

Fig - 2: Graph plotting of Accuracy and Loss for Sequential CNN

After training, the confusion matrix for the validation data has been obtained. A confusion matrix is an N x N matrix utilized for assessing the performance of a classification model, where N is the quantity of target classes. The matrix compares the actual target values with those anticipated by the model. The confusion matrix has also been plotted for the validation dataset consisting of 1488 images. It has been observed that Actinic Keratosis has maximum number of correct predictions. The confusion matrix is as follows:

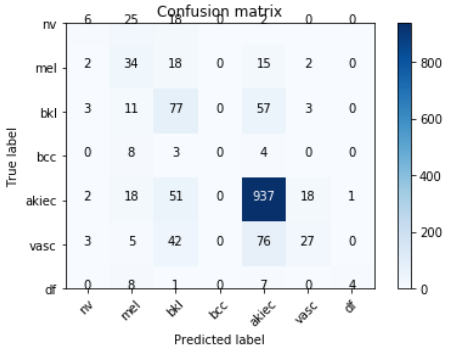

Fig - 3: Confusion Matrix obtained after evaluating the Sequential CNN model

MobileNet CNN:

After training the model for 30 epochs, overall accuracy has been found to be 84.22% while top2 and top3 accuracies are 92.54% and 96.40% respectively. The loss and accuracy curves are displayed below:

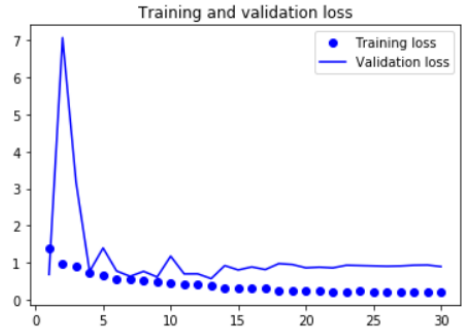

Fig – 4a: Training loss vs. Validation loss for MobileNet Model

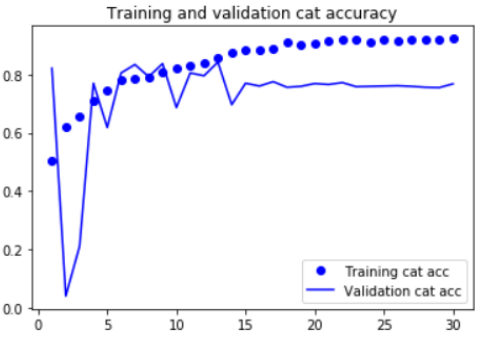

Fig – 4b: Overall Training accuracy vs. Validation accuracy for MobileNet Model

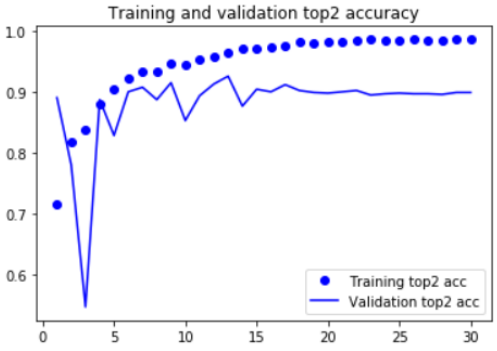

Fig – 4c: Top2 Training accuracy vs. Validation accuracy for MobileNet Model

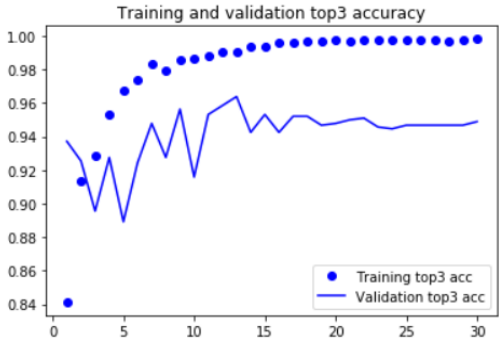

Fig – 4d: Top3 Training accuracy vs. Validation accuracy for MobileNet Model

Here, a matrix has been plotted for 938 images present in the validation dataset. It has been observed that Melanocytic Nevi has maximum number of correct predictions.

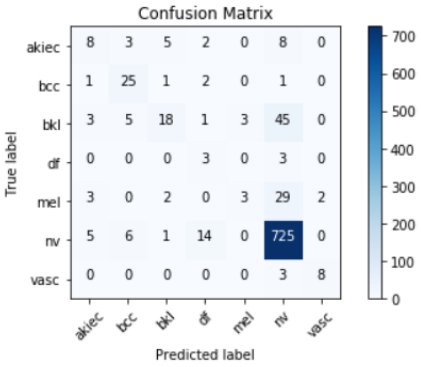

Fig -5: Confusion matrix obtained after evaluating the MobileNet model

Also, following values have been calculated for each class of skin lesions:

Recall = Given a type, will the classifier be able to differentiate it properly?
Recall = True Positive/ (True Positive + False Negative)

Precision= Given a type prediction from a classifier, how probably is it to be right?
Precision=True Positive/(True Positive + False Positive)

F1 Score = It can acquire the properties of both precision and recall. Basically, it rejects extreme values.
F1- score = 2((Precision*Recall) / (Precision + Recall))

Class Wise values have been displayed for the validation dataset.

	precision	recall	f1-score	support
akiec	0.40	0.31	0.35	26
bcc	0.64	0.83	0.72	30
bkl	0.67	0.24	0.35	75
df	0.14	0.50	0.21	6
mel	0.50	0.08	0.13	39
nv	0.89	0.97	0.93	751
vasc	0.80	0.73	0.76	11
avg / total	0.83	0.84	0.82	938

Fig-6: Classification report obtained after evaluating MobileNet model

3.1 Pitfalls

One of the major disadvantages of the MobileNet Neural Network is the huge number of trainable parameters. It has more than 4.2 million trainable parameters. Due to this sometimes the model based on MobileNet architecture may fail to generalize or may overfit. Also, sometimes MobileNet networks may train at a very slower pace due to its larger architecture weights.

3.2 Conclusion

The recognition of cancer in beginning phases can be of very assistance to fix it. In view of the literature, execution of the different CNN models will assist with understanding which can be the most proficient one compared to others as far as speed and accuracy is concerned. Also, the proposed research work can come handy in situations where human help is not accessible very easily. Consequently, it will be the focal point of the following phase to develop such an application which will be proficient enough for the clinical field to depend on.

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