Enhanced Melanoma Classifier with VGG16-CNN

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Introduction

Melanoma has arisen as a major public health challenge in recent decades (Schadendorf et al., 2015). Melanoma is the most severe kind of skin cancer, yet it can be treated if detected early. Melanoma develops when melanocytes, the pigment-producing cells present in the skin, eye, inner ear, and leptomeninges, develop genetic abnormalities (Domingues et al., 2018). Despite accounting for only around 1% of all skin malignant tumors, cutaneous malignant melanoma is the most aggressive and deadly type of skin cancer. The rising incidence rates and mortality rates of melanoma have prompted a renewed focus on early identification and prevention]. Dermoscopy greatly enhances the diagnostic accuracy of the naked eye examination, according to several meta-analyses. However, dermatologists and medical practitioners who were professionally trained in various dermoscopic algorithms had an average sensitivity of about 80% for identifying melanoma.

Artificial intelligence has recently been shown to be capable of categorizing images of benign nevi and melanoma with dermatologist-level precision, according to recent articles. Higher model performance correlates with a large number of images, however, it is not always cost-effective to run a large number of image datasets with a deep learning network. It is pertinent for us to see ways to cushioned more image datasets with the training model used.

Convolutional neural networks (CNNs) have been utilized in recent research in digital skin diagnostics to categorize melanoma images with accuracies comparable to those attained by dermatologists (Nasr-Esfahani et al., 2016; Perez et al., 2019). Prior studies used a huge number of images to train their algorithms, which were then confirmed by consensus decisions. When photos are validated in this way, there is a strong chance that the CNN will learn the dermatologists' decision-making process, including all probable errors.

The rising incidence rates and mortality rates of melanoma have prompted a renewed focus on early identification and prevention. This work focuses on Melanoma amongst 9 classes of Skin cancer (see Fig. 1)

Figure 1: Illustration of (a) Benign lesions, (b) Melanoma lesions (Mendonça et al., 2013)

Methods

Datasets

The Dataset is provided by SIIM ISIC (Rotemberg et al., 2021). The dataset was made available for download as part of a live competition on the Kaggle platform from May 27, 2020 through August 20, 2020. It's licensed under the Creative Commons Attribution-Non Commercial 4.0 International (CC BY-NC 4.0) license and can be found at <https://doi.org/10.34970/2020-ds01>. This comprises of 2297 Image datasets belong to 9 classes of Images lesions: which are 'actinic keratosis', 'basal cell carcinoma', 'dermatofibroma', 'melanoma', 'n

evus', 'pigmented benign keratosis', 'seborrheic keratosis', 'squamous cell carcinoma', 'vascular lesion'.

Figure 2: Classes of images from the train set by ISIC

Preprocessing with VGG16 library has a preprocessing function specific to the VGG16 model `keras.applications.vgg16.preprocess_input` which seems to do additional steps like subtracting the average RGB channel values of the original ImageNet training set. In this paper, we present a model for classifying melanoma based on the DNN presented by Visual Geometry Group with 16 layers (VGG16). First, we pre samples as byteplot pictures, in which each byte represents one grayscale pixel. Using the convolutional layers of VGG16 pre-trained on the ImageNet dataset, we extract the filter activation maps (also known as bottleneck features) by deducting the average RGB channel values of the original Image net and adjust the training set images.

Project Framework

This framework illustrated how we arrive at a faster model with high accuracy for training melanoma lesion images. In this work, we used VGG16 and CNN architecture.

- Collate the datasets
- Preprocess the images with VGG16 by extracting the features and labels
- Set the parameters or fine-tuning the images and environment for the CNN model
- Train the images with CNN
- Evaluate the model with accuracy as the metrics

Figure 3: Architecture of the VGG16-CNN Model

Implementation

- We used an approach similar to (Mamiya & Miyata, 2020) in which authors first preprocess images with vgg16 and used it to denoise the input images and

generate unlabeled images that was trained with CNN. Our hyper parameter configurations are the following:

- Image preprocessing: Image data generator (Chollet, 2016)
- Learning rate: 0.0001
- Pooling: max pooling with stride 2
- Loss: Binary cross entropy
- Optimizers : Adam
- Training Model: Sequential Cov2D
- Epochs : 10
- Verbose: 2
- Metrics: Area under curve (AUC) (Bradley, 1997)

Figure 4a: AUC showing Training and validation Accuracy

Figure 4b: AUC showing Training and validation Loss

Area under Curve (AUC) metric of 93% was achieved which indicated a very high accuracy melanoma classifier. The results also showed that there was no over fitting because of the decline in training and validation loss (see figure 4a&b).

Results

In this work, we have studied:

- Preprocessing images with VGG16
- Training images with CNN
- Classification of lesion images into Melanoma and Non melanoma (see figure 5). The results were classified correctly when matched up with the ground truth.

Figure 5: Classification results into Melanoma and Not Melanoma

Conclusion

We have developed a Melanoma Classifier, which achieved a performance accuracy of 93%, precision of 1 and recall of 0.5% with Melanoma images, through preprocessing images with VGG16. Overall, this indicated that training images need

to be preprocessed before they can be trained on deep learning models especially when aiming at higher performance accuracy.

Future Recommendation

The test datasets for Melanoma was very few compared to the other classes of skin cancer lesion images, which affected the recall and the F1 score of the predicted test images.

GitHub

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