ISIC 2019
Skin Lesion Analysis Towards Melanoma Detection

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Abstract

ISIC 2019 is a skin lesion image classification challenge from dermascopic images organized by the International Skin Imaging Collaboration [1, 2]. In this manuscript, we describe the methods we used to create our submission for this challenge.

1 Introduction

Skin cancer is a major public health problem, melanoma being the deadlist form of it. The number of melanoma cases in 2015 is estimated to be 350,000 with almost 60,000 deaths. The survival rate with early detection exceeds 95% [1]. Hence early detection is extremely important and algorithms that can improve the ability to screen high resolution dermascopic images are very valuable.

2 Task

The first task of ISIC 2019 is to classify images of skin lesions. The diagnostic categories are as follows:

1. Melanoma
2. Melanocytic nevus
3. Basal cell carcinoma
4. Actinic keratosis
5. Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis)
6. Dermatofibroma
7. Vascular lesion

8. Squamous cell carcinoma

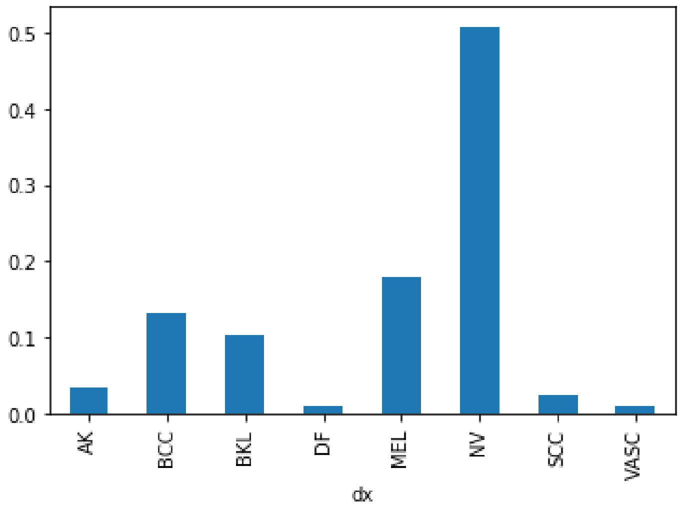
9. None of the others

The second task consists of performing the same classification from images with the addition of meta data.

3 Data

The training data consists of 25,331 dermascopic images across 8 different categories [3, 4, 5]. There are no images in the training data for the 9th category, the outlier class, however the algorithms are expected to identify this category in the test data. For the second task, in addition to the image data, meta data is provided as well.

The categories in the training data is highly imbalanced. The relative frequencies of each category is given as follows:



To avoid the effects of this, we applied a stratified training/validation split with validation size 2000 and used a weighted loss with class weights computed using ‘compute_class_weight’ function from sklearn.utils [6].

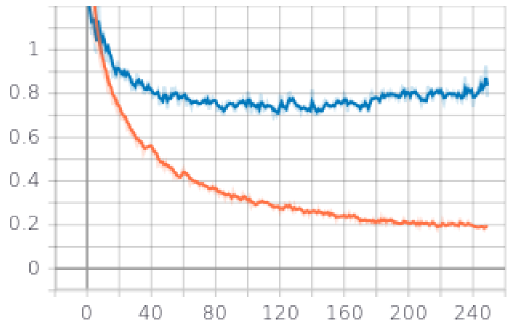
4 Model

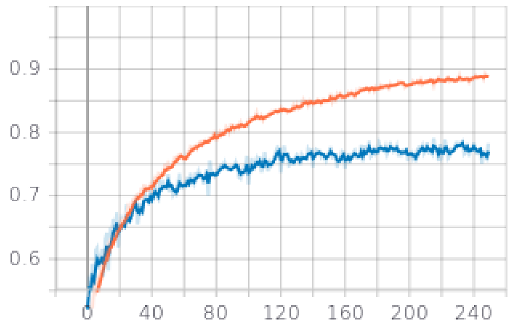
We have implemented our model in Tensorflow 2.0 using tf.keras [8]. Our model architecture is simple. We used transfer learning with the pre-trained DenseNet201 [7] trained on imagenet with average pooling. In order to reduce training time, we first feed the data into DenseNet201 and saved the bottleneck features as TFRecords. As a result, we were able to train the classifier on top with these bottleneck features. This let us run the training on a CPU in a reasonable time and tune the hyperparameters.

The classifier consists of the following layers:

- BatchNormalization
- Dropout with rate 0.5
- Dense layer of size 2048, relu activation and L2 regulariozation with 1e-15
- BatchNormalization
- Dropout with rate 0.5
- Dense layer of size 1024, relu activation and L2 regulariozation with 1e-15
- Dense layer of size 8 with softmax activation.

For the training we used a batch size of 128 and the Adam optimizer with the default learning rate of 0.001. The loss and categorical accuracy on the training and validation data is shown in the below figures where blue curve corresponding to the validation data and the orange curve corresponds to the training data. The balanced accuracy on the validation data is 0.745.





Note that the output layer has dimension 8 corresponding to the conditional probabilities of the provided classes in the training data. For the outlier class we simply applied a threshhold value of 0.35. So we predict the outlier class if the maximum probability of the output of softmax is less than 0.35.

Finally we applied the following sigmoid conversion to create binary classification confidences

$$\frac{1}{1 + e^{-a(x-b)}}$$

with $a = 3.5$ and $b = 0.15$

References

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