TB3 : Image and Pattern recognition 2019-20
Project -Automatic classification of skin lesions (melanoma detection)-

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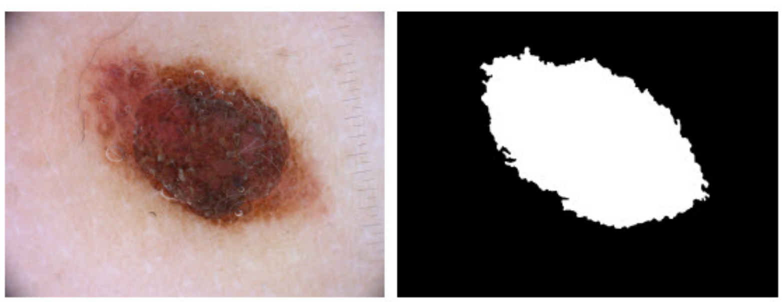
The objective of this project is to propose a methodology for the automatic classification of skin lesions, based on image analysis and machine learning.

1 PART 1 : Description of the Database and pre-processing

Here is a sample of the images we are willing to process (Original image of skin lesion and the segmented image) : Figure 1



(a) original image (b) segmented lesion

FIGURE 1 – Database sample

We dispose also of the segmentation of the original images using super-pixels, these last ones will be used later with geometrical descriptors on Python.

Our database is composed of 200 samples, which are part of a 2000 original database from the world wide challenge : "ISIC 2017 : Skin Lesion Analysis Towards Melanoma Detection". The images' names are not ordered and a complex reading system was coded into MATLAB in order to load all of these images and assign to each one of them their corresponding labels, the script attached to this report is well commented explaining every part of this process.

The loading step has been done twice, in MATLAB and Python since I used both of them to classify the images. Here is a sample from the Database loaded and labelled in Python : Figure 2

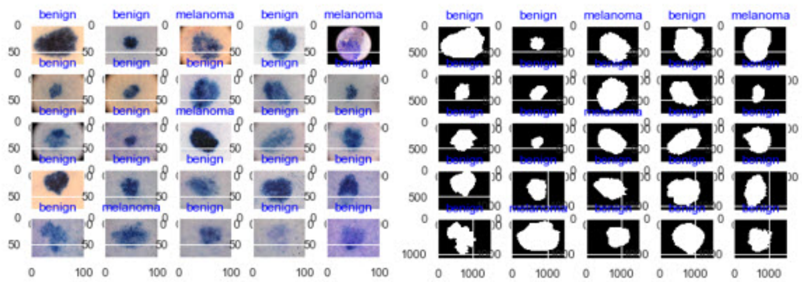


FIGURE 2 – Labelled images from Database

We will now take profit of several machine learning models in order to achieve a good accuracy in our classification problematic, the steps of the different methods used will not be detailed as much as in the first project, still the scripts attached are very well commented.

2 Classification using texture descriptors (LBP) :

The Local Binary Patterns (LBP) descriptor is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number, the details of the descriptor were seen in course. For a given image of a skin lesion, I computed the LBP histogram for its three components (Red, Green and Blue), the result is the following Figure 3

We can see that the three histograms are almost superimposed, so for the classification we will only use one of them, this allows us to reduce significantly the complexity of our model since we will have only 255 descriptors instead of 765.

The LBP descriptor is then computed on the first (red) component of all images in our database, we now have a representation of the individuals (images of skin lesion) in a 255 dimensions space.

The next step is splitting the population into training and test sets just like the first project, 4 classifiers are then trained on this Data with automatic Hyper-parameters optimization : Decision trees, Knn, Discriminant analysis and a naive Bayesian classifier (I tried to use binary classifiers that were not used before).

Using the function *metrics* I coded, I then compute the accuracy and FScore for each one of these classifiers and plot them into a *bar-plot* in order to decide

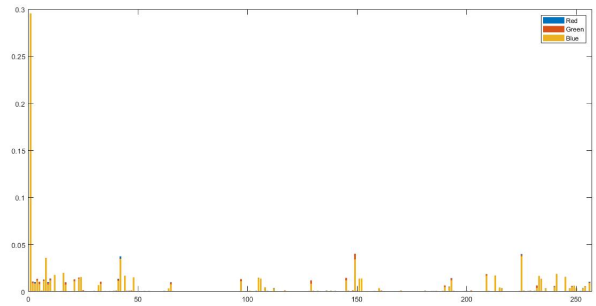


FIGURE 3 – LBP histogram of three color components of the skin lesion image

of the best one among them, this gives the following Figure 4

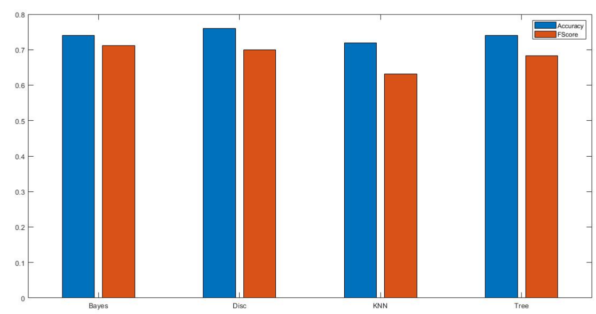


FIGURE 4 – Accuracy and FScore of each classifier

The discriminant analysis Classifier is the best one among the 4 used with the following scores :

$$Accuracy = 76.0000\%$$

$$FScore = 0.7000$$

The corresponding Confusion Matrix and ROC curve : Figure 5

The accuracy we got with this model is not very satisfying, hence we are going to try more efficient classifiers on the next section.

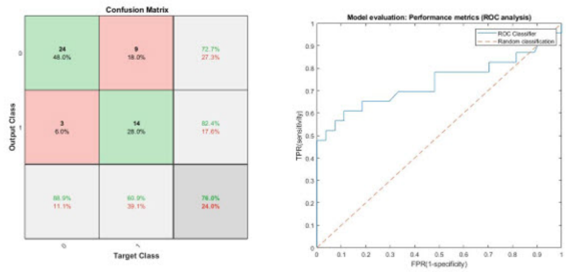


FIGURE 5 – Confusion matrix and ROC curve for the discriminant analysis classifier

3 Classification using geometrical descriptors (RegionProps) + Color irregularity (number of superpixels) :

Analogically with the first project, the geometrical descriptors will be computed on the segmented images. Just like MATLAB, Python has a library *skimage.measure* that contains a function *regionprops_ table* that computes all possible geometric descriptors for binary images : area, bbox_area, convex_area, eccentricity, equivalent_diameter, extent, major_axis_length, minor_axis_length, perimeter.

```
props = sm.regionprops_table(train_images[i], ...
     properties=['area', ...
     'bbox_area','convex_area','eccentricity','equivalent_diameter',
'extent','major_axis_length','minor_axis_length','perimeter'])
```

In order to reduce the complexity of the classifier, I used the Python library *sklearn.feature_ selection*, and exactly the function *SelectKBest* to select the 5 best features from the 9 we had, this reduces the number of the space's dimensions and help improve the rapidity of the classifier.

```
%I will select only the best 5 best features among the 9 computed
imgdata_new = SelectKBest(chi2, k=5).fit_transform(imgdata, ...
     train_labels)
%I won't go into details but the chi2 metric is adequat for the ...
     classification problem
```

A sixth feature is then added to the obtained features' matrix : It's the number of superpixels computed by analyzing the three components (Red, Green and Blue) of the given superpixels image.

At this step our Data is ready to go into classifiers, the same splitting is performed again (75% Training Data and 25% test Data). I am going to use 5 classifiers : Logistic regression, Decision tree, Gradient descent, Gradient boosting and Knn.

The data we have is really not sufficient for an efficient classifier, 200 hundred images is not enough, hence, for a credible accuracy value I used cross-validation on 10 samples for every model, the mean value of the accuracy' values obtained is considered to evaluate the classifiers then.

The accuracy results are as following : Figure 6

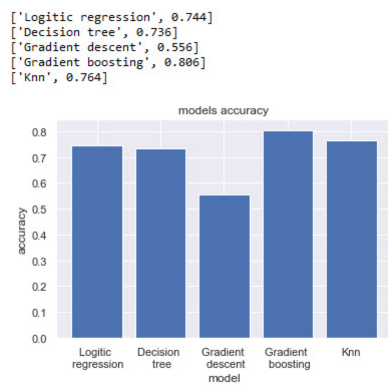


FIGURE 6 – Accuracy of the different classifiers used

$$Accuracy = 80.6000\%$$

The best model is the Gradient Boosting model, with about 80% (around 75% before adding the number of superpixels as a feature) accuracy on 10 sampling data using cross-validation. The idea that comes to mind next is combining the geometric descriptors, the texture descriptors (LBP done on MATLAB) and the color irregularity feature wich is the number of superpixels, unfortunately I didn't have the time to test it since it requires a considerable pre-treatment before running it into Machine learning models.

4 Classification using a CNN (Convolutional neural network) :

In papers about the original challenge, I read that the best accuracy values (>95%) were obtained using deep learning, so as a bonus method, I decided to use a CNN in order to classify the images.

The biggest problem is that we have really few images, so after splitting the Data we have (112 training images, 50 test images, 38 validation images) which is not enough to evaluate the CNN's performance and decide of the accurate values for its hyper-parameters.

Another problem is the high dimensions of our images (767*1022*3), so passing through a Convolutional layer is like an infinite operation for a normal laptop. To encounter this issue I used only one component of the image resized to smaller dimensions (84*112) as input images even if this would remove a considerable part of the information contained in the images.

The details of the layers used and the values of the parameters of this model are in the attached script which is well commented.

The accuracy plot for training and test Data gave the following : Figure 7

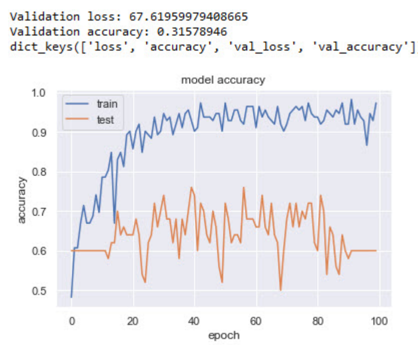


FIGURE 7 – Training and test accuracy

Our CNN can achieve very high training accuracy (96%), but still fails with the test Data, since we have not enough Data it is difficult to know the reason behind this issue and correct it, it could be simply by chance due to the low number of test images, same remark for the validation accuracy which is computed on a even smaller set of images.

A sophisticated visualization with the percentage of belonging to each class in the next Figure : 8

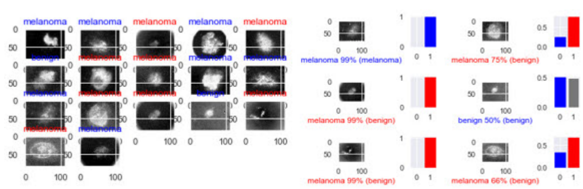


FIGURE 8 – Prediction on the validation set

Even if it was not very successful in our case due to many reasons, a CNN well settled can be very efficient in an image classification problem.