Face alignment using deep learning

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1 introduction

For a long time work in facial recognition has being done and one of the key points of it is face alignment as it poses its own challenge. And the main tool used for the job is OpenCV which is used with DLIB to recognize Facial landmarks.

The automatic recognition of landmarks is essential to be able to classify facial expressions, or face tracking, face animation, and even 3D face modeling.

For example to classify facial expressions it is necessary to classify Facial Action Units also known as FACS [1], which in turn needs a proper face alignment.

The problem of face alignment is among the most popular in the field of computer vision and today we have many different implementations to automatically recognize facial landmarks on images. The most known is the Active Appearance Model (AAM) [2, 3].

But today we also some good results using Deep learning to achieve the results for example the work done by Adrian Bulat on recognizing 3D facial landmarks [4] that shows remarkable results and is implemented in *Torch* a framework for **LUA**.

As the DLIB model has difficulty on recognizing points on faces by the side view, this project focus on this problem and does its best to tackle this problem.

2 Dataset

In this study the MUCT Face Database [5] was used this dataset consists of pictures (resolution 480x640) taken from 276 subjects using 5 cameras in different angles and light conditions (total of 3755 images) like the image below:

Each picture is manually coded with 76 facial landmark like:

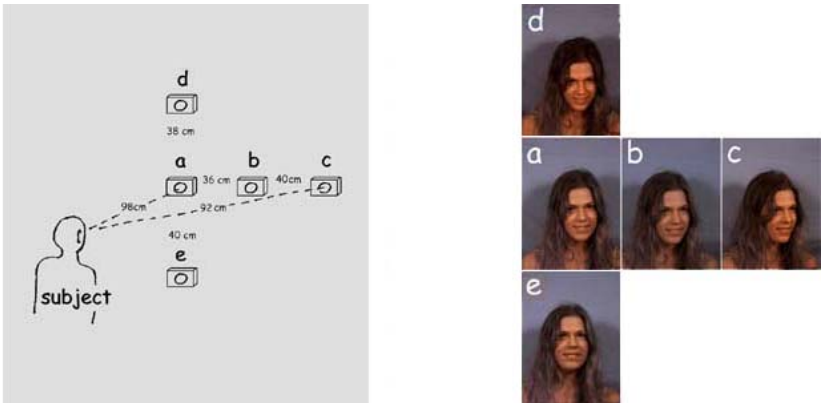
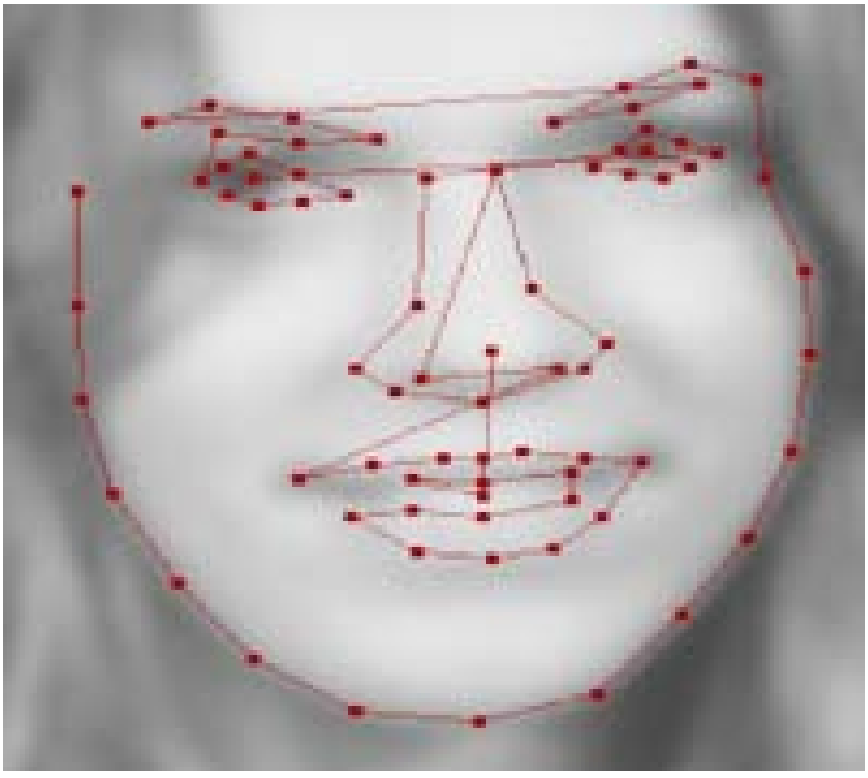


Figure 1: There is no images on the left but they can be reproduced by mirroring the right side



The landmarks are saved in to 4 different file formats

- muct76.shape shape file [6]

- muct76.rda R data file (www.r-project.org/
- muct76.csv comma separated values
- muct76-opencv.csv comma separated values in OpenCV coords (0,0 at top left).

the coordinate system in these files is the one used by Stasm (i.e. the origin 0,0 is the center of the image, x increases as you move right, y increases as you move up). The exception is muct76-opencv.csv, where the format is the "OpenCV format" (i.e. the origin 0,0 is at the top left, x increases as you move left, y increases as you move down).

Unavailable points are marked with coordinates 0,0 (regardless of the coordinate system mentioned above). "Unavailable points" are points that are obscured by other facial features. (This refers to landmarks behind the nose or side of the face – the position of such landmarks cannot easily be estimated by human landmarkers – in contrast, the position of landmarks behind hair or glasses was estimated by the landmarkers).

So any points with the coordinates 0,0 should be ignored. Unavailable points appear only in camera views b and c.

the subjects 247 and 248 are identical twins.

The data set is available via github or it is also a submodule on this project and by recursively initializing or cloning the data can be found in folder project/dataset that is the recommended way as the scripts depend on this folder

2.1 Split the training and testing sets

As this dataset is composed by multiple images of the same subject the division of sets for training and testing could not be done at a random way as an special attention is needed to not have the same subject on the train and testing set.

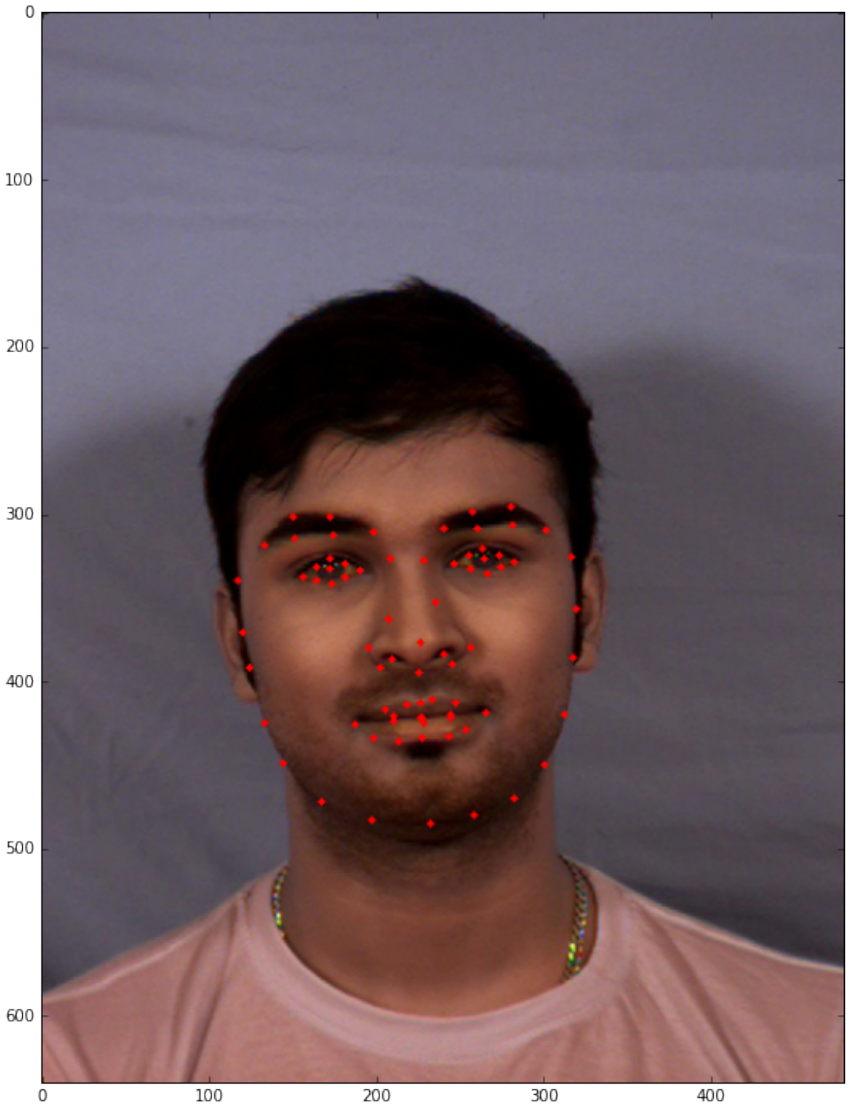
And after analyzing it was divided by taken the first 82 subjects for the testing set (249 images per camera total of 1245 around 30%)

The function "decompress$_{\text{dataset}}$" on the *DataGen.py* takes care of decompressing the data and splitting the training and testing set.

2.2 Data Analyses

lets start by looking at one image from the database those images are on the format of 640x480.

And lets plot the points on one image to have an insight:



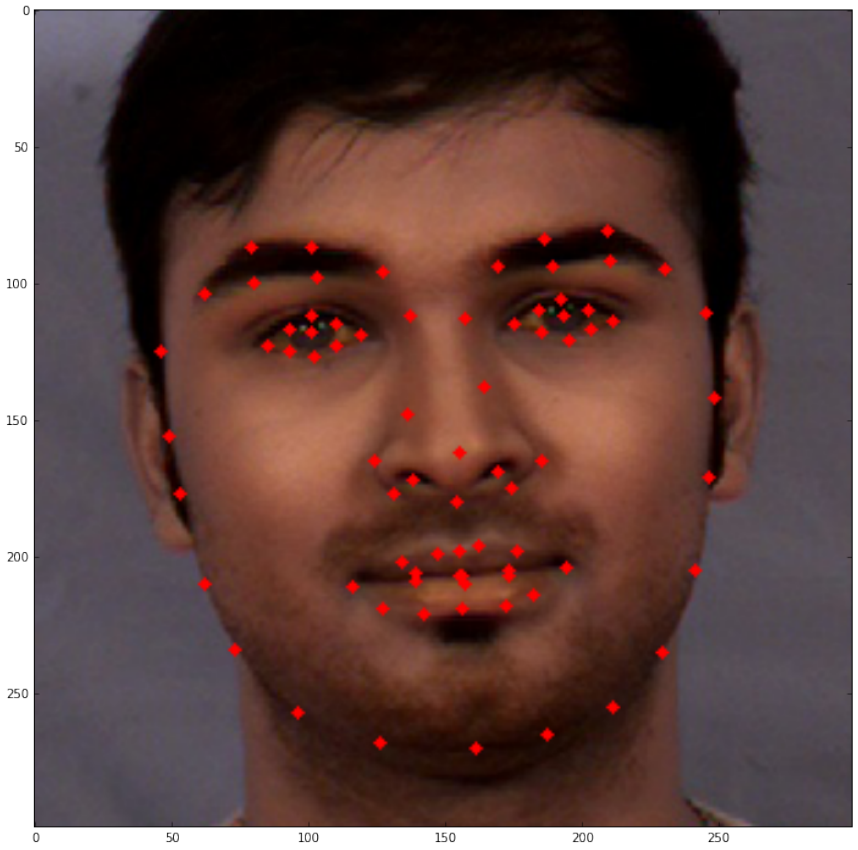
As is possible to see those images are large and have big regions with useless information like the background.

To improve that lets use DLIB's face recognition to find the face area and crop it, for that we can use the function "crop$\backslash_{\text{image}}$" from the *DataGen.py* this function takes the image and the size to crop we pass just one integer for the size as it crops the image in a square, and returns the cropped image and the bound box used to crop the image.

But as the image have being cropped we also have to move the land-

Figure 2: image cropped with the size of 299 x 299.

mark points to match the new image, for that we can use the function "replace\landmarks" which takes the bound box and the actual landmarks and return the new landmarks



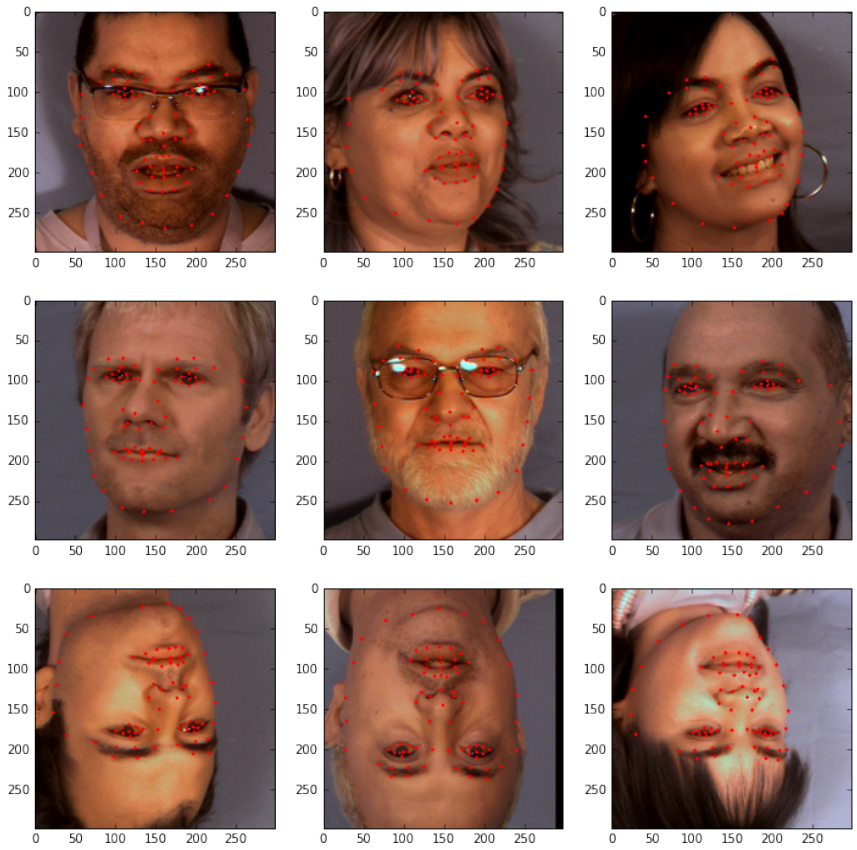
the process of cropping the image brings 2 advantages to the project:

- less resources needed to train model
- it makes possible to use images with more than one face in the future

2.3 Data Augmentation

As explained before there is no cameras on the left but we can mirror the right images, starting from that we will implement a some data augmentation like flipping every image horizontally and vertically.

To achieve that we can use the function "flip$\backslash_{\text{image}}$" also from *DataGen.py* it takes the image, the landmarks, the direction to flip, width and height. and returns the new image and landmarks. lets see the result:



By applying this to all images we finish with a total of 3723 testing images and 7497 training images

3 Models

For this project many different approaches have being taken and it will be presented here the best outcome of each "kind" of approaches like:

- A CNN created from scratch
- Inception transfer learning

- ResNet50 transfer learning

All the models have being trained in a cloud server for performance wise and saved to later study.

The metrics used to observe the performance of every model was the mean square error (MSE)

The models code can be found on the file *Models.py*.

The models use a *"npz"* file that can be generated via by using the function :

```
DataGen.save_dataset(DataGen.create_dataset(size, True, True), "outputName")
```

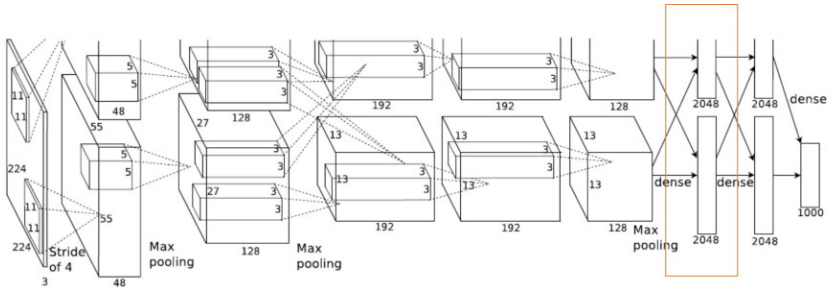
And for the inception transfer learning it uses a bottleneck file that can be generated with the function:

```
DataGen.inception_bottleneck(<npz file>, "outputName")
```

every model was implemented using early stopping, TensorBoard and saves the best loss weights on a *hdf5* file

3.1 CNN from scratch

This CNN started with a model based on the AlexNet [7]



But we finished with a model as illustrated below:

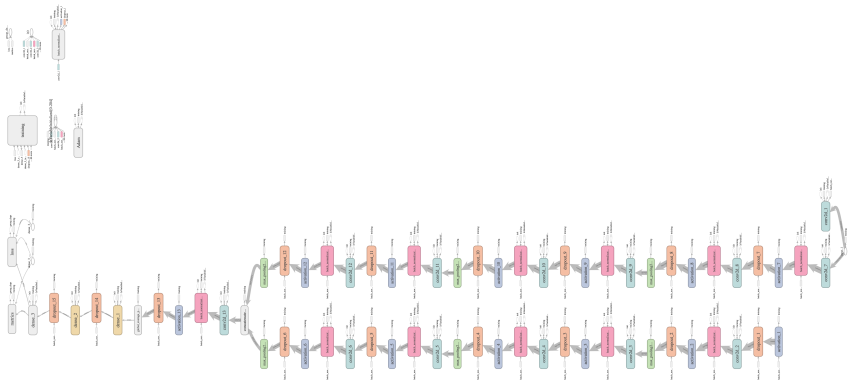
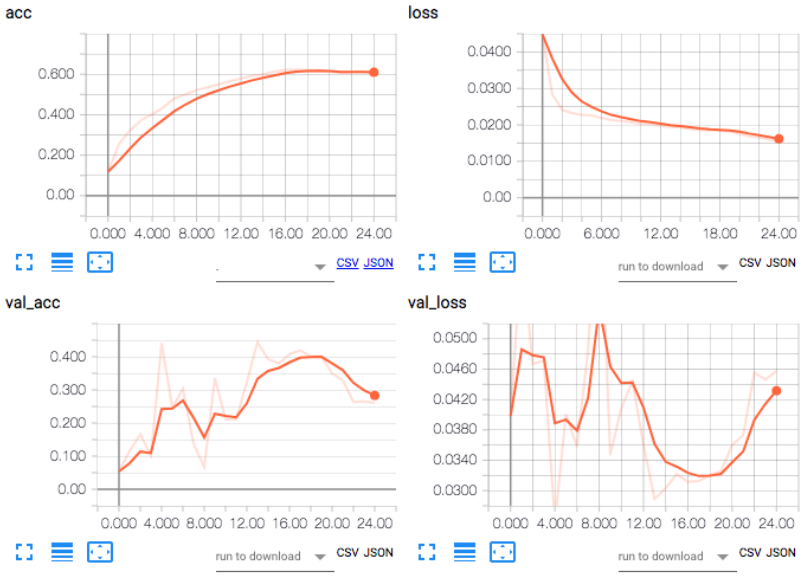


Figure 3: the full size image can be found on the report/images/mymodel.png.

here is the learning curve from this model



as we can see the learning curve for the training set was improving steadily but for the testing set it starts to get worst around the epoch 16 and the early stopping is triggered at epoch 24 as it has no improvement.

by taking the weights of the best loss and doing an inference on a set of training images we get the following result:

It is noticible that the result is not satisfactory but it has plenty of room for improvement. but at this point of the project it started to get expensive to keep using the cloud machine to train and there was yet some other methods to try out.

3.2 Inception transfer learning

3.2.1 bottleneck

The next step was to use transfer learning, by using the inceptionV3 [8], the first approach as to create bottleneck files from the inception and train a model with those outputs.

As the previous model many models have being made and here is the best result found by using this method was the following:

In this model we took a different approach as just using the output of Inception wasn't given good results 3 different inputs was used the squared

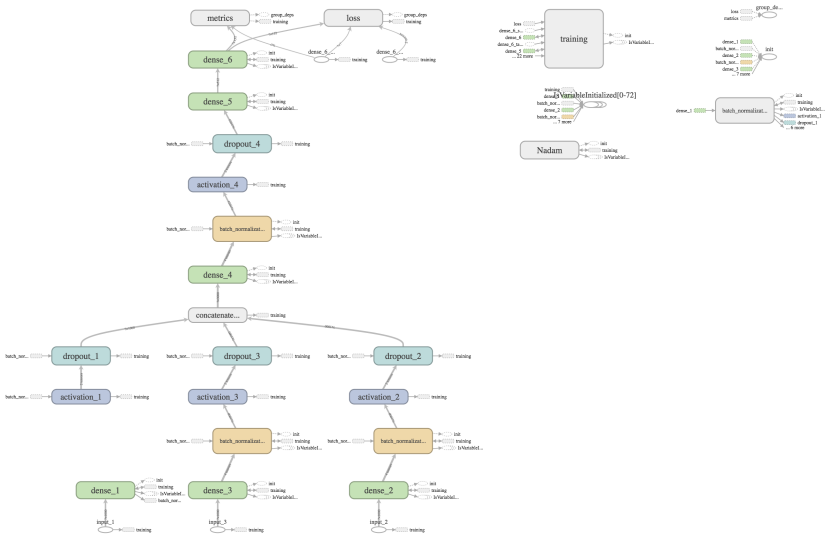
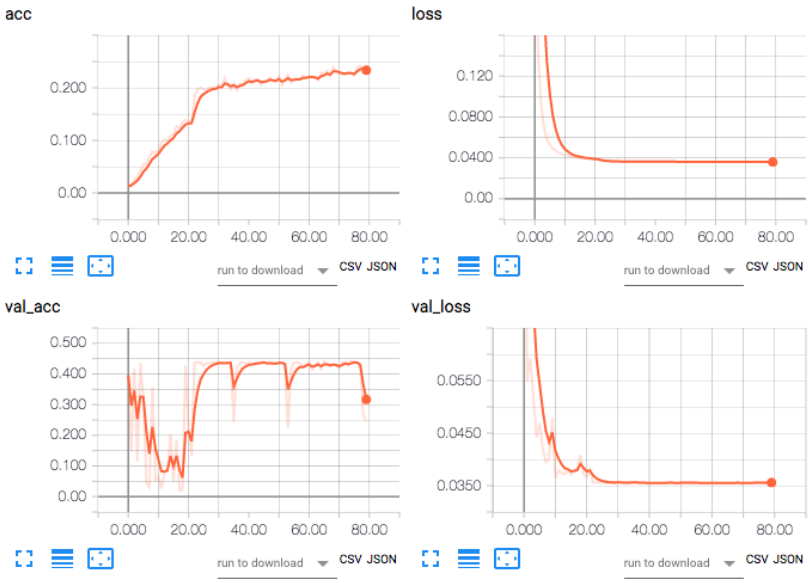
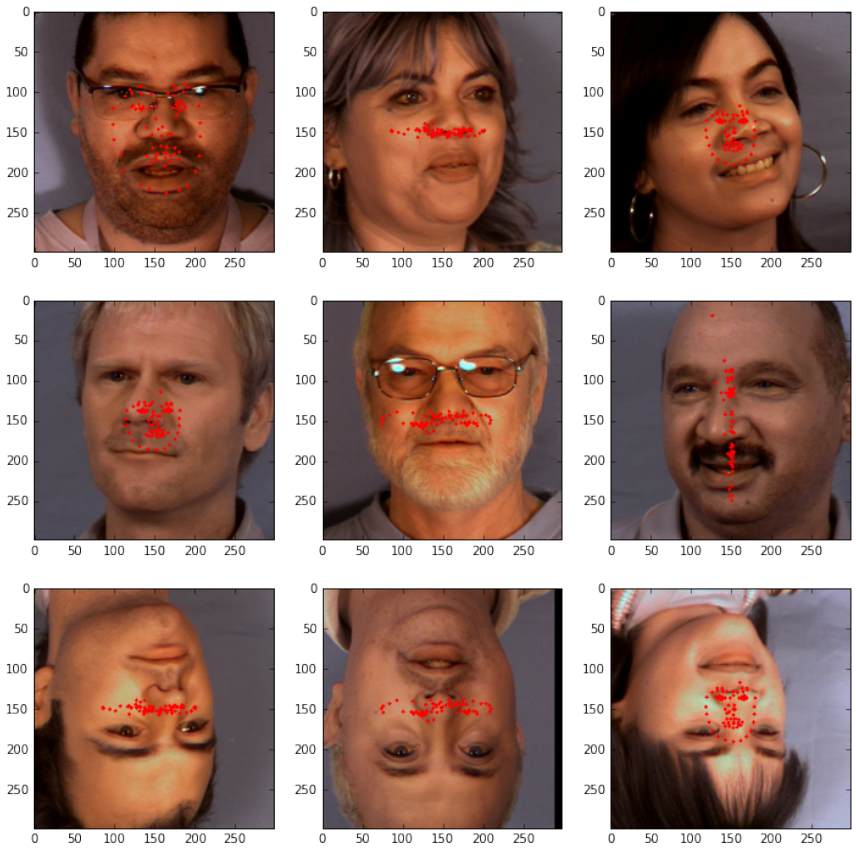


Figure 4: the full size image can be found on the report/images/btn.png.

and the *sine* of the inception output was also used in conjunction to the normal output



The training of this model took 80 epochs before the early stopping was triggered while the learning curve on the test set is better them the previous model the loss is slightly bigger them the previous model:



And the results are far from good, worst then the previous model.

3.2.2 Retrain

The next step here is to keep using the transfer learning from inception but give a bit of more room for improvement by training respectively the 2 last convolutional blocks of the inception and the 4 last ones:

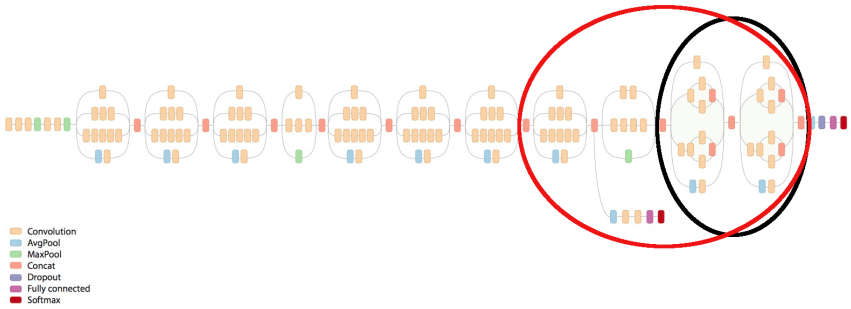
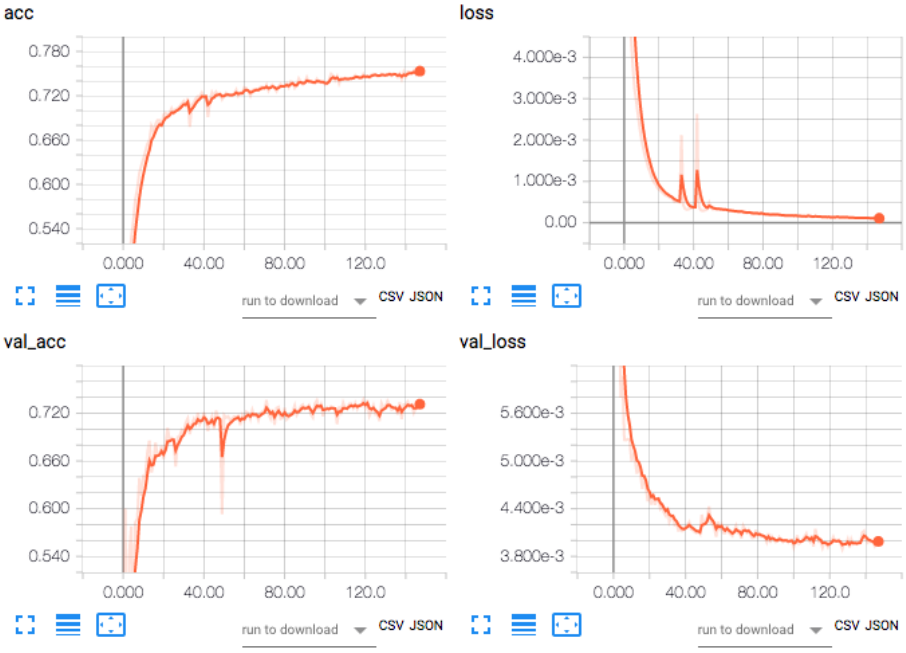
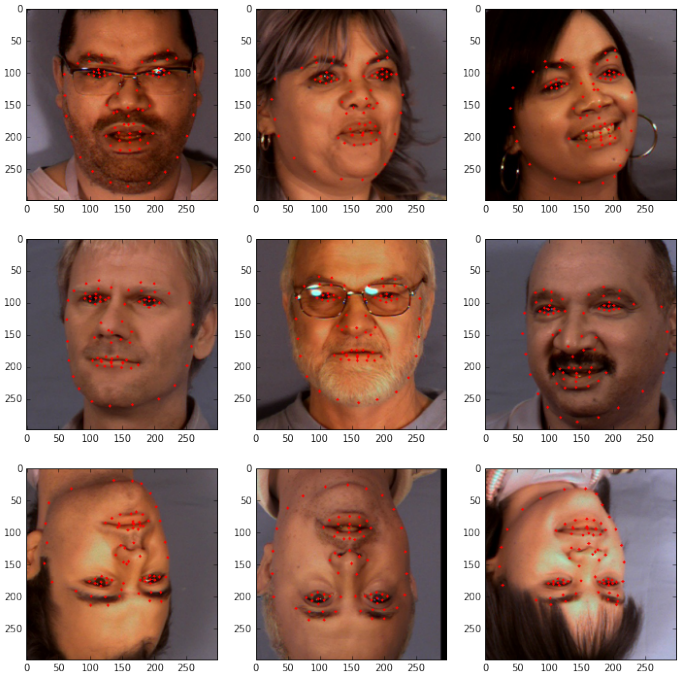


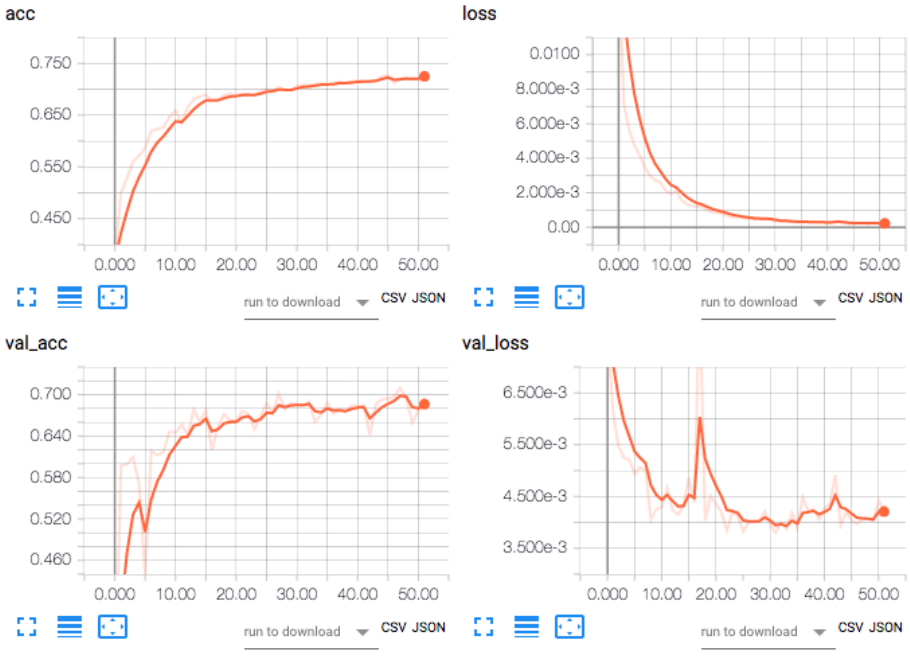
Figure 5: 4 block(red) 2 block(black).

1. **2 blocks results**





2. **4 blocks results**

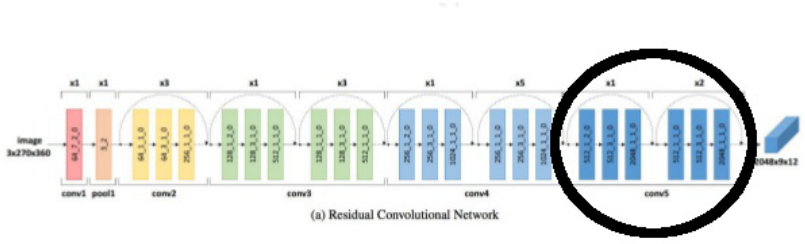


as we can see it really improved the results by using the 2 first blocks after a 120 epochs we have a steady learning curve and we get a nice prediction on the testing images, but once we increase the number of training layers by using the first 4 block, the early stopping triggers 70 epochs before and while the results look good, however, it is worst then the model with 2 blocks.

3.3 ResNet50 transfer learning

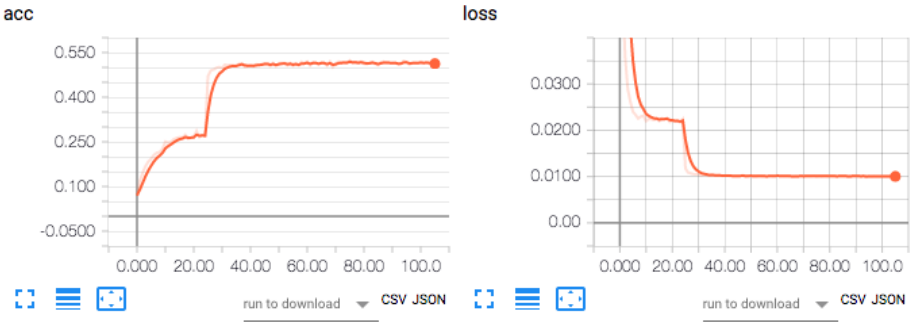
Here the same approach that as used with Inception is used with the ResNet50 [9] model, but as the ResNet50 uses images with format 224x224 and we have images with 299x299, while we could crop the images it is not a good solution as it was cutting out landmarks from some images. So the idea here is use the ResNet50 with different input.

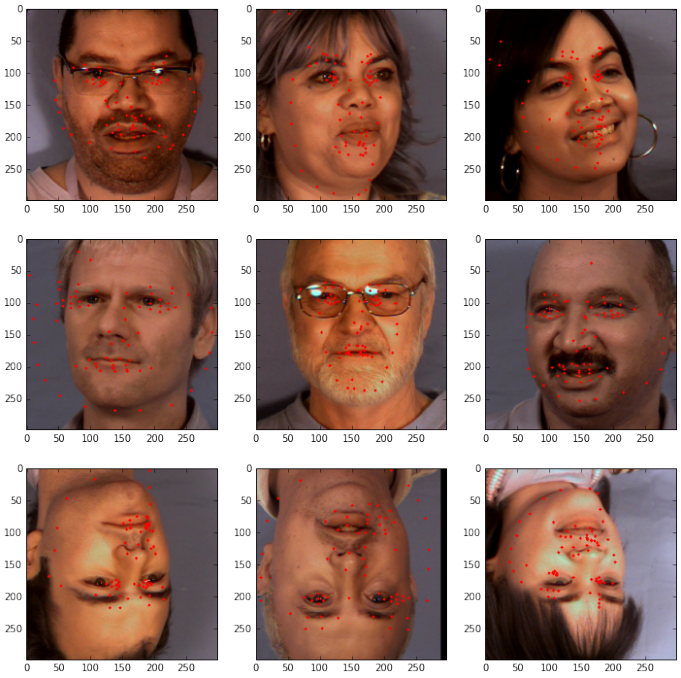
2 models was trained here one that don't train any layer from ResNet50 and another that trains 2 convolutional blocks like:



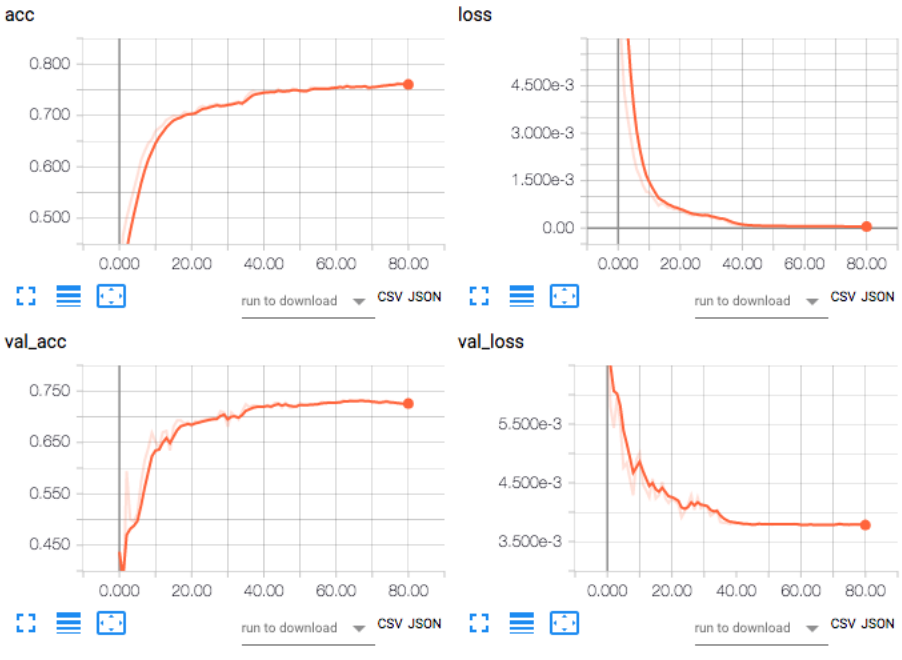
ResNet-50

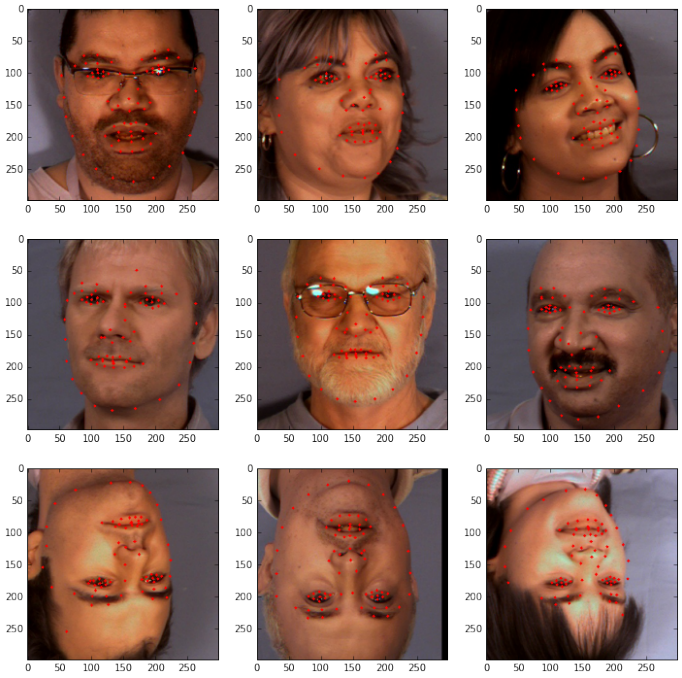
1. **0 blocks results**





2. **2 blocks results**





as it is noticible using just the output of ResNet50 did give better results them the inception but yet it wasn't satisfactory in the other hand when retraining 2 block it showed a really promising result

4 Results

after all those tests and trials we can make a loss comparison for each model like:

model	training loss	validation loss
scratch	0.01547	0.02588
inception bottleneck	0.03599	0.03567
inception 2 blocks	0.0001108	0.003932
inception 4 blocks	0.0002229	0.003802
resnet50 0 blocks	0.01	0.013
resnet50 2 blocks	0.00005033	0.003779

by doing this comparison we see that the ResNet50 model has the most promising results and probably is possible to get even better results by training more layers or even making some adjustments, but as this kind of training demands a lot of resources and keep the servers running started to get out of the budget the tests and development where halted at this point

5 Conclusion

This project shows that the approach used is correct and that with more resources is possible to delivery a reliable face alignment. The next step on such a project would be by starting by using some other datasets in conjunction to the MUCT so we can get a better generalization as all the images on this set has the same background it can bias the result.

And also by working on the hyper-parameters for the ResNet50 network and improving the results that would a start for getting a reliable face alignment

6 Hardware

For information propose all the training was executed on a virtual server hosted on google cloud The specs are the following:

8 CPUs with 60GB of memory and 1 NVIDIA Tesla P100 for the price of $1490.51 per month at a rate of 2.042 per hour

References

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