Project report
Deep learning: binary image classification

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1. Task

The task is to implement a deep-learning-based system discriminating between real faces and comics, using the *Comics faces* dataset. This dataset is published on Kaggle and released under the CC-BY 4.0 license, with attribution required. It contains 10.000 real-face images and 10.000 comics-face images in 1024x1024 format.

2. Introduction

This report will briefly explain the process undergoing the creation of a well-performing binary classifier. The chosen deep-learning system is the Convolutional Neural Network (CNN), a class of Artificial Neural Networks, largely applied to analyze visual imagery. The report will cover all the relevant parts of the algorithm implementation: data organization and preprocessing, creation of the CNN, model selection, and the discussion of the results.

3. Data

3.1. *Dataset*

The *Comics faces* Kaggle dataset is composed of 20.000 face images: 10.000 real faces images and 10.000 comics faces images in 1024x1024 format. The real faces and comics faces images are paired: for each real image, there is the comics version.

3.2. *Data organization*

The complete dataset has been used to train, validate and test the models. It has been downloaded directly from *Kaggle* to *Google Colab* using the *Kaggle API*. The Jupyter Notebook attached to this report is directly executable on *Google Colab* by loading your *Kaggle API Token* in the designated code cell. To each downloaded image, a label has been applied: 0 for real faces and 1 for comics faces. Then, the images have been separated from the labels and respectively stored in an X and y variable.
After being preprocessed (see Subsection 3.3), the complete dataset, composed of pairs image-labels, has been split into two sets: *Training Set* and *Test Set.*
From the training set *(x_train, y_train)* two smaller training set has been created to speed up the computation for the Grid Search. The first subset of the training set *(x_train_try1, y_train_try1)* composed of 4800 examples is used in the first round of model selection for training 27 models.
The second subset of the training set *(x_train_try2, y_train_try2)* composed of 10.800 examples is used in the second round of model selection for training 6 models. I decided to implement this system of subsets of the training set to be able to try a larger number of models in the available time. In the second round, a larger number of examples is used because the best models could be different for different training set sizes.
The training set is further split in each training session in Training Set and *Validation Set*. The validation set is automatically created by *Tensorflow* to plot the performances of the trained models and perform model validation.

3.3. *Preprocessing*

The 1024x1024 images have been reshaped into 150x150 images for computational and storage capacity issues. This specific shape has been selected, after different manual visualizations, because the images remained reasonably detailed and the size is not too large.
For the same reasons, the images have been processed in grayscale.
The entire dataset has been shuffled. This is very important because initially our images are sequentially ordered for each category. This would lead the CNN to learn "always predict 0 and at a certain point 1", leading to terrible performances on new data.
The last preprocessing step consists in scaling the images such that their pixel

values are normalized between 0 and 1. This makes the work a lot easier for the CNN.

4. Algorithm implementation

4.1. *Convolutional Neural Network*

The Convolutional Neural Network is a Neural Network to which a convolutional layer has been added. This technology is very powerful when processing images because it can extract features from images. The convolutional layer, through a filter that scans (convolves) the pixel of the images, can detect patterns: the deeper you go with the convolutions, the most likely is that the patterns become features of the images. Working with face images it would probably start from very easy shapes like lines and circles ending up with noses, eyes, mouths, and so on. Each convolutional layer is associated with a pooling layer (typically max pooling) which is needed to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters to learn and the amount of computation performed in the network.
For this reason, the CNN was the most reasonable choice for the task

4.2. *how the proposed solution scales up with data size?*

The CNN I modeled, and more in general all the code I wrote in the Jupyter Notebook, easily scale up with data size. Indeed, to process a larger number of examples you only need greater computational and storage resources. For example, using Google Colab you only need to pay for larger memory space and faster GPUs.

4.3. *Model structure*

All the models I trained have a common structure and only some hyperparameters have been tuned.

Common structure:

- Every model has at least 1 convolutional layer
- Every convolutional layer has a 3X3 window
- Every convolutional layer is associated with a Relu activation function

- Every convolutional layer is associated with a 2X2 Max Pooling layer
- Every model has a Flatten layer after the convolutional layers
- Every model has a final dense layer of size 1 and a final Sigmoid activation function
- If a model has additional dense layers they are associated with a Relu activation function
- Every model uses a binary crossentropy loss function
- Every model uses Accuracy as the metric
- Every model uses Adam Optimizer for the learning rate

While many of the parts composing the common structure are simply chosen because they are efficient choices used in the literature for this kind of classifier, some of them could have been tuned. Only some Hyperparameters have been tuned because of the resources (time, computational, storage). The values chosen for the other optimizable Hyperparameters are simply standard choices.

Adam Optimizer is almost always used to optimize the learning rate based on the momentum of the Stochastic Gradient Descent making the computation more efficient
The Relu activation function is a non-linear function whose main advantage is that it does not activate all the neurons at the same time. It is more computationally efficient than the Sigmoid function (Another natural choice). For this reason, the Relu function has been used for each internal layer, while the Sigmoid function has been only used at the final step.
The Flatten layer is needed to convert from the 2-dimensional output of the convolutional layer to the 1-dimensional input of the dense layer.
The binary crossentropy loss function and the Accuracy metric are simply obvious choices for this task.
The 3X3 size of the convolutional window and the 2X2 size of the max pooling layer, as well as the choice of a max pooling as pooling layer, are standard choices I decided to use.

4.4. *Model Selection*

To train all the Hyperparameters for a large number of values was definitely not a feasible path. To decide which kind of Grid Search to perform I previously experimented with a few, almost randomly, chosen values for 2 epochs.

The results lead me to some reasonable values for the three Hyperparameters I wanted to tune: the number of convolutional layers, the size of the layers, and the number of additional dense layers.

Values used for the first Grid Search:

- Number of Convolutional layers: 1, 2, 3
- Layer sizes: 32, 64, 128
- Number of additional dense layers: 0, 1, 2

To train and evaluate on the entire training set all the 27 models that are output by this *Grid Search* a very large amount of time is required. I decided to perform the model selection through two rounds of Grid Search.

For the first round, I used the first subset of the training set *(x_train_try1, y_train_try1)* composed by 4800 examples. On this small dataset, all 27 models have been evaluated for 10 epochs and using 30% of the data as the validation set.

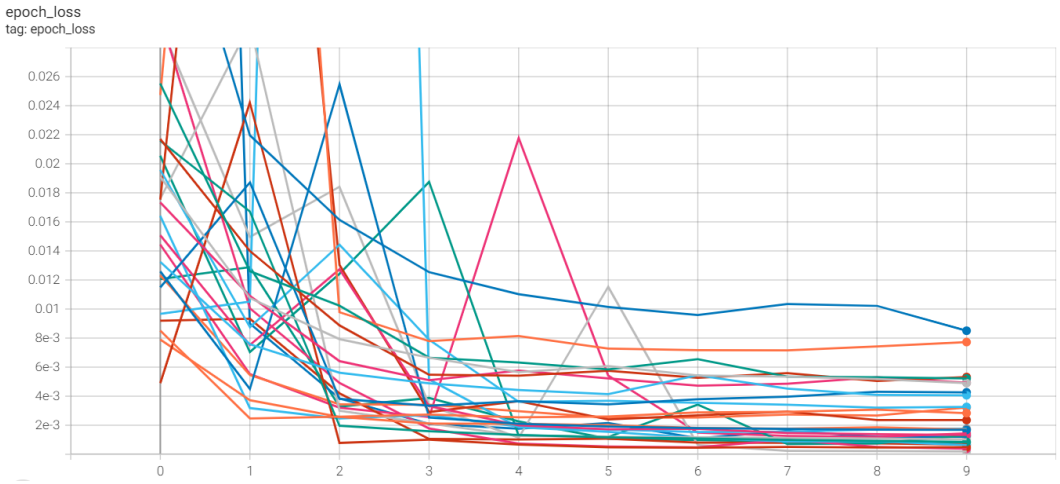


Figure 1. First round validation loss by epochs- 27 models using 4800 examples

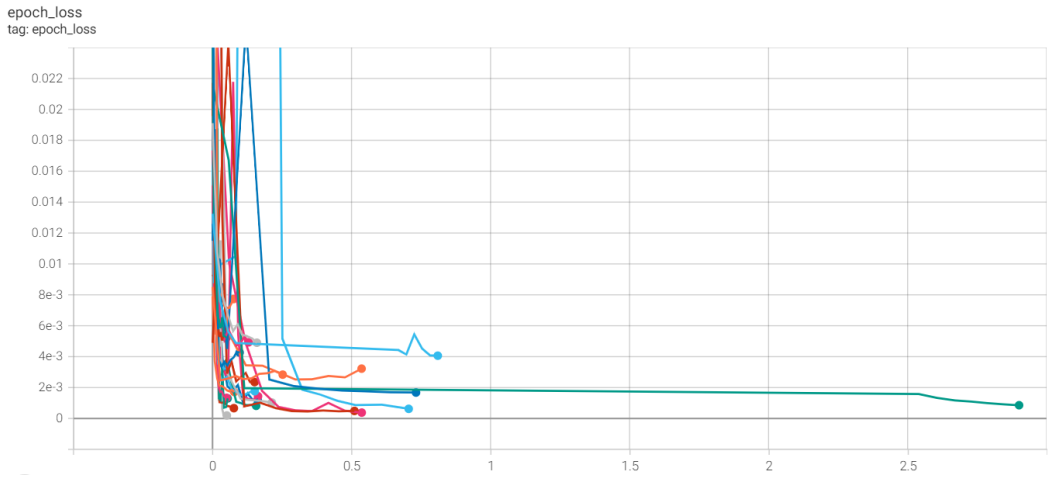
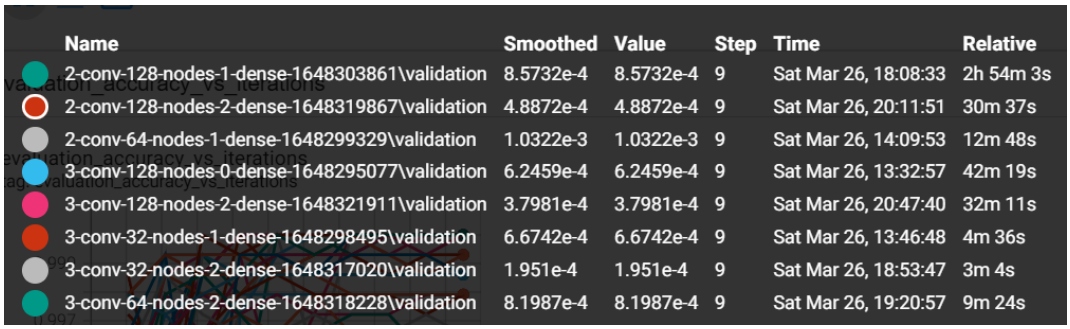


Figure 2. First round validation loss by time- 27 models using 4800 examples



Name	Smoothed	Value	Step	Time	Relative
2-conv-128-nodes-1-dense-1648303861\validation	8.5732e-4	8.5732e-4	9	Sat Mar 26, 18:08:33	2h 54m 3s
2-conv-128-nodes-2-dense-1648319867\validation	4.8872e-4	4.8872e-4	9	Sat Mar 26, 20:11:51	30m 37s
2-conv-64-nodes-1-dense-1648299329\validation	1.0322e-3	1.0322e-3	9	Sat Mar 26, 14:09:53	12m 48s
3-conv-128-nodes-0-dense-1648295077\validation	6.2459e-4	6.2459e-4	9	Sat Mar 26, 13:32:57	42m 19s
3-conv-128-nodes-2-dense-1648321911\validation	3.7981e-4	3.7981e-4	9	Sat Mar 26, 20:47:40	32m 11s
3-conv-32-nodes-1-dense-1648298495\validation	6.6742e-4	6.6742e-4	9	Sat Mar 26, 13:46:48	4m 36s
3-conv-32-nodes-2-dense-1648317020\validation	1.951e-4	1.951e-4	9	Sat Mar 26, 18:53:47	3m 4s
3-conv-64-nodes-2-dense-1648318228\validation	8.1987e-4	8.1987e-4	9	Sat Mar 26, 19:20:57	9m 24s

Figure 3. First round validation loss data - best 8 models using 4800 examples

By inspecting the performances of these 27 models on Tensorboard we can draw some considerations.

Models without any additional dense layer are completely unstable.
All the completely unstable Validation Loss curves displayed in Figure 1 correspond to models without any additional dense layer.

Models with 128 as layer sizes have very large training duration without too much improvement. All the Validation Loss curves with the longer training durations displayed in Figure 3 corresponds to models with 128 as layer sizes.

Models with only 1 convolutional layer show bad performances and models with 3 convolutional layers are the best
Indeed we can see in Figure 2, which displays the best 8 models performances, that no models with only 1 convolutional layer appear. Moreover, models with 3 convolutional layers prevail.

For the second round, I used the second subset of the training set *(x_train_try2, y_train_try2)* composed of 10.400 examples. On this dataset 6 models have been evaluated for 8 epochs (I realized that after 8 epochs no relevant improvement happened) and using 20% of the data as the validation set.

Values selected for the second Grid Search based on previous considerations:

- Number of Convolutional layers: 3
- Layer sizes: 32, 64, 128
- Number of additional dense layers: 1, 2

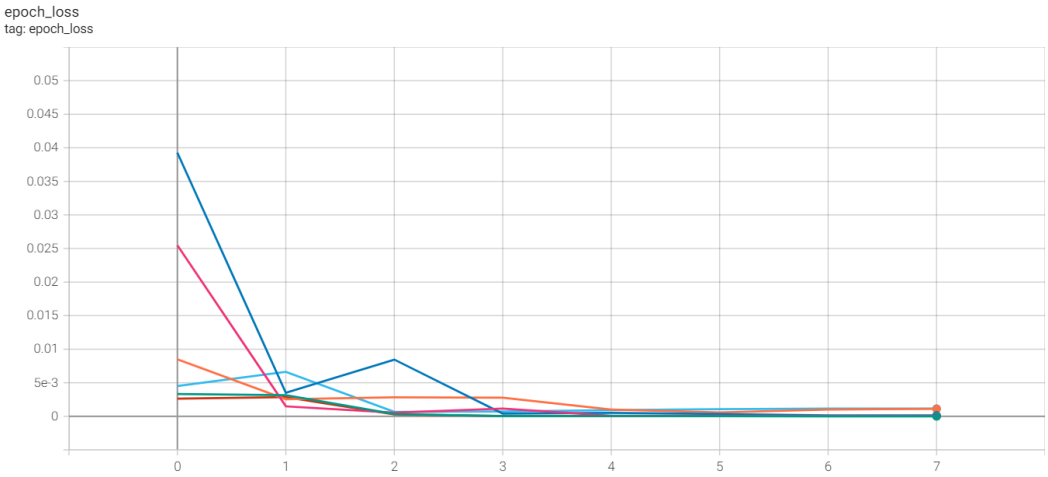


Figure 4. Second round validation loss by epochs- 6 models using 10.800 examples

Not including models with zero dense layer was a good choice: all the models are now stable as we can see in Figure 4.

The best 4 models in terms of validation loss are:

1. **3 Convolutional Layers, Layer sizes 128 and 1 dense layer**. Very large training duration: 1h, 34 min and 18 sec
2. **3 Convolutional Layers, Layer sizes 64 and 2 dense layers**. Quick training duration: 18 min and 25 sec
3. **3 Convolutional Layers, Layer sizes 128 and 2 dense layers**. Large training duration: 1h, 5 min and 33 sec
4. **3 Convolutional Layers, Layer sizes 32 and 1 dense layer**. The fastest for training: 6 min and 36 sec

These 4 best models have been trained on the entire training set *(x_train, y_train)* composed of 16.000 examples for 10 epochs.

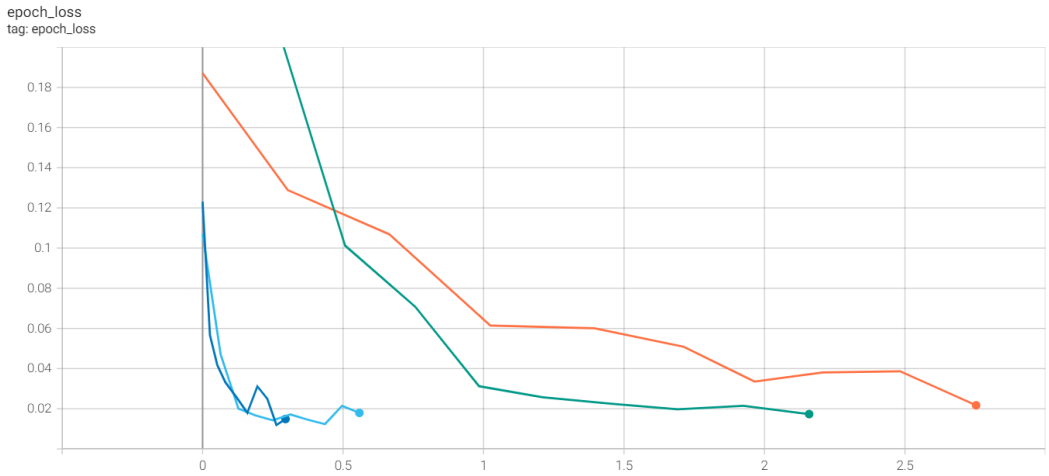


Figure 5. Third round validation loss by time- 6 models using 16.000 examples

Looking at Figure 5 we can notice that the best two models, the ones with 32 and 64 as layer sizes, are also by far the faster in the training session. These two models will be my 2 final models to be tested on the test set.

4.5. *Can we further improve our models?*

With a larger dataset, we could have improved our trained models. However, we don't have it.
Instead, something we could have done is a deeper Hyperparameters tuning.
I have only performed model selection on a few Hyperparameter values. For this project, we didn't have either the computational capacity or the time to perform a larger Grid Search.
However, based on what we learned from previous steps, there is something we can try.
We know that the layer sizes can not be enlarged for time resources and that it seemed not to improve performances too much. Excluding the case with zero dense layers, this Hyperparameter value (the number of dense layers) alone seemed not to change the performances.
The number of convolutional layers instead could be a leading factor in model per-

formances.

We can try our best-performing model (3 conv, 64 layer sizes, 2 dense) with 4 or 5 convolutional layers!
Indeed, they perform even better than our best models.
The last attempt I want to do is to see if reducing the layer sizes of the model with 5 convolutional layers would reduce the training duration without worsening the accuracy: we try 5 convolutional layers, 32 as layer sizes, and 2 dense layers.

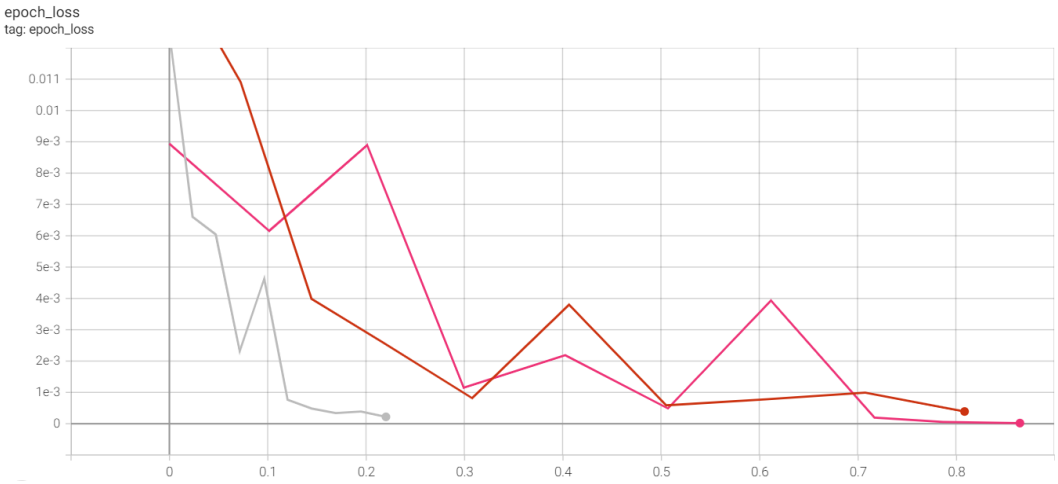


Figure 6. Experiment with more convolutional layers - validation loss by epochs - 3 models using 16.000 examples

As we can see in Figure 6 that the last model I experimented, is by far the fastest. Moreover, it is only slightly worse performing than the best one.

4.6. *Testing the models on the Test Set*

After the training, the 3 best models have finally been tested on the test set *(x_test, y_test)* composed of 4000 examples. Their performances are represented by the test loss, the test accuracy, and the number of misclassified images:

- **4 Convolutional Layers, Layer sizes 64 and 2 dense layers**.
  test loss: 0.25084
  test accuracy: 0.99924
  It misclassified only 3 comics faces as real faces and nothing else

- **5 Convolutional Layers, Layer sizes 64 and 2 dense laye**r.
  test loss: 0.05063
  test accuracy: 0.99975
  It misclassified only 1 comics faces as real faces and nothing else
- **5 Convolutional Layers, Layer sizes 32 and 2 dense layers**.
  test loss: 0.05555
  test accuracy: 0.99975
  It misclassified only 1 comics face as real face and nothing else

5. Conclusions

In conclusion, a larger number of convolutional layers could be tested. Other technologies could have been added to try to improve the performance.
A typical choice for this kind of model is to add a Drop Out Layer. It is used to prevent overfitting from happening. I didn't include it because I had no overfitting issues.
The best model I trained is the last one because it has slightly worse performance than the same model with 64 as layer sizes, but it is a lot faster to train.

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