

Classification of painter's artwork

Convolutional Neural Network

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Vision and perception course

Chosing and ideating project

- The idea behind the theme of the project came from the necessity to re-discover the artistic aspect of life that surrounds us. So instead of let them vanish we decided to create something that could be educationally useful
- Our network classify the painting of ten different artists: Caravaggio, Dalì, Escher, Gentileschi, Gonsalves, Magritte, Monet, Rembrandt, Renoir, Van gogh
- The realization was done using the open source library Tensorflow and its API Keras

Workflow pipeline

- Our goal was to tune correctly the parameters of a model such that it could be train to map a particular input to an output. To do that we followed some steps:
 - Find the dataset of interest
 - Build the dataset on Tensorflow
 - Build the model
 - Train and test the model
 - Improve it and repeat the process
- To do that we made use of some python libraries such as os, numpy, matplotlib, PIL

Chosing image dataset

- We selected 100 images per painter, without repetition
- Each image were collocated in the right folder
- The size of the image was handled by a specific function: `aspect_ratio_resize_smart`
- At this point, every image will have a side of 256 and the other side is calculated so that the aspect ratio is unchanged

Creating Dataset

- Building the dataset in Tensorflow require the use of the `tf.data` API
- The dataset is created taking all properly resized images from the directories with the help of the method : `tf.data.Dataset.list_files(path)`
- In order to have the dataset of the form: (image, label), the name of the folder was exploited
- `Get_label`, `decode_img` and `process_path` are function used to obtain this labeled dataset
 - `Get_label` takes the name of the folder from the path
 - `Decode_image` decode the image back to proper format
 - `Process_path` take the image and calls the other two functions

Training set

- The total amount of images are divided into training and test set, taking 4 over 5 images for the first one
- Each image of the training set are manipulated with the `augment` function, used to create augmented data; with the following characteristic:
 - `Random_crop`
 - `Random_flip_left_right`
 - `Random_brightness`
 - `Random_saturation`
 - `Random_contrast`
 - `Random_hue`
- This set is prepared for the training phase with some property of `tf.data.Dataset` such as `.cache`, `.shuffle`, `.repeat`, `.batch`, `.prefetch`

Test set

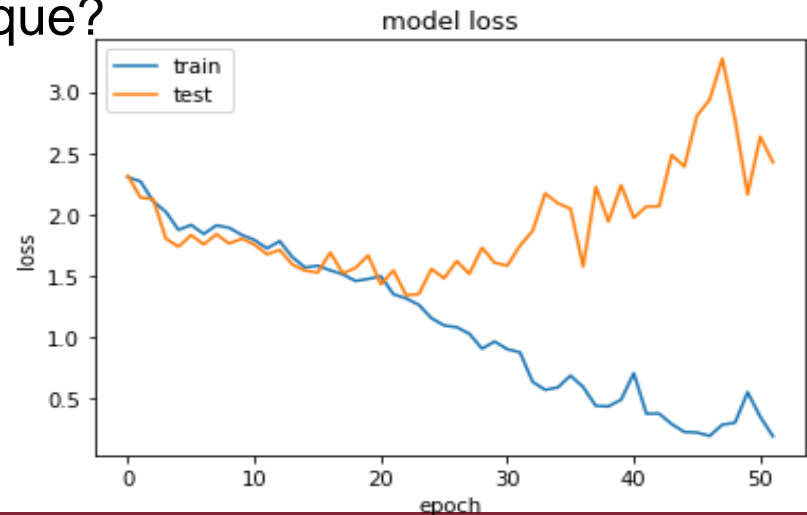
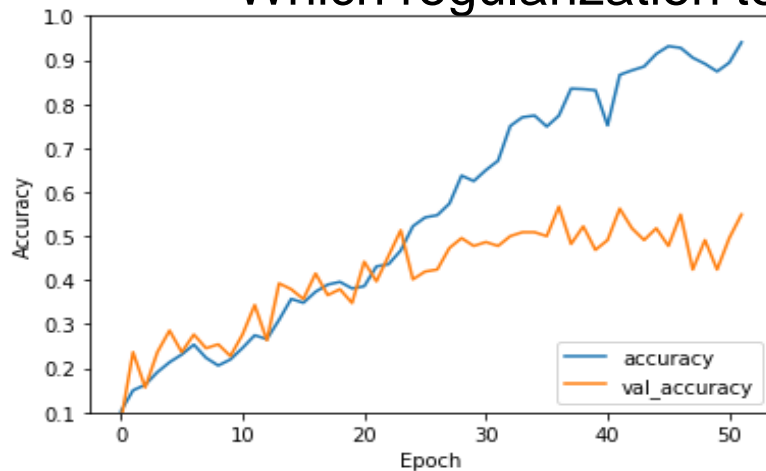
- The test images are centrally cropped
- Another possibility is to resize the whole image
- The augmentation data is not needed for the testing phase
- This set to be prepared for uses the same property listed for the training
- The defined BATCH_SIZE for both training and test is 32

Convolutional Neural Network

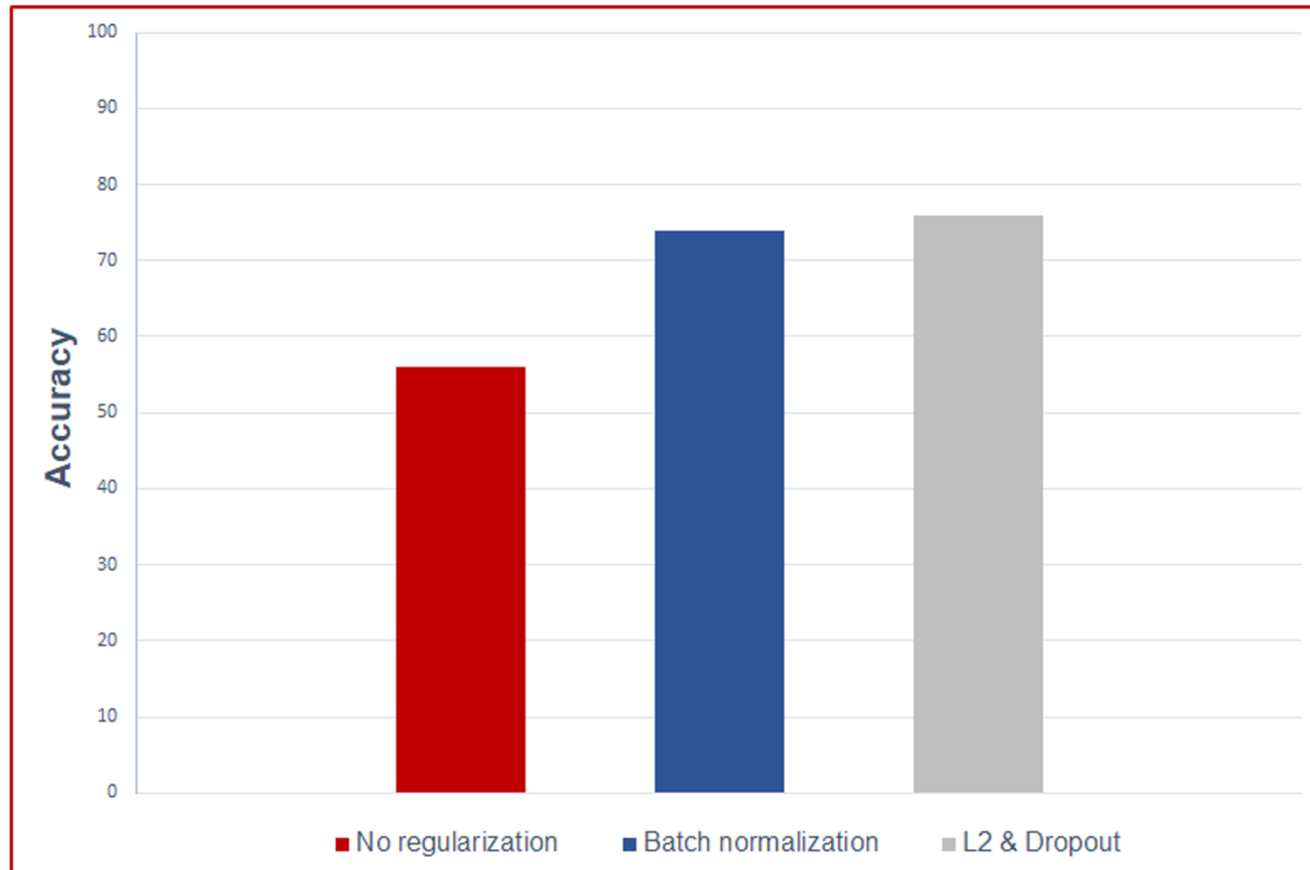
- This type of network takes its name from the most critical component of the architecture that is the convolutional layer
- Conv nets are divided into 4 components
 - Convolution
 - Non Linearity
 - Pooling
 - Classification
- To construct our own model we had to choose the best parameters to be given at each component

CNN from scratch

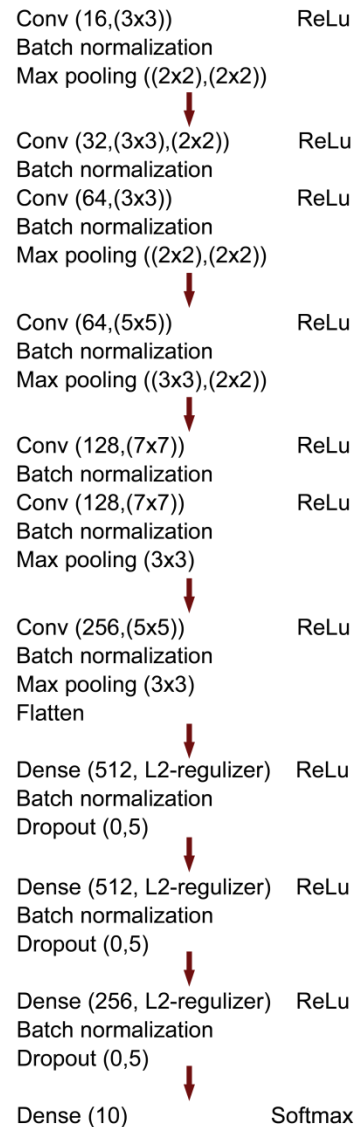
- To create a model we had to make several decision:
 - How many filters to use and of which size?
 - How to use padding or stride?
 - Which type of non-linearity?
 - How many layers?
 - What about the activation values?
 - Which regularization technique?



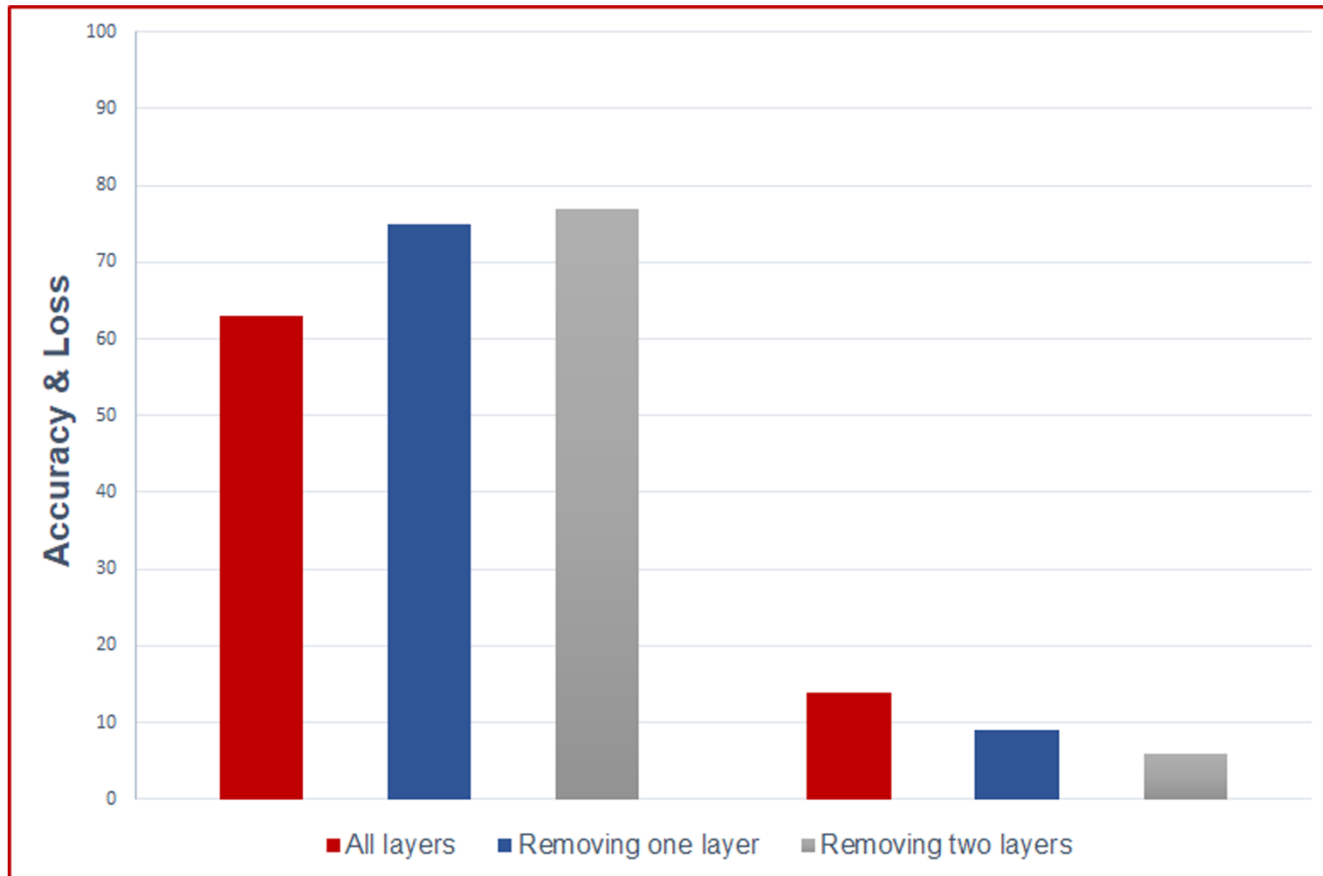
Regularization improvement



CNN architecture



CNN from scratch with less data augmentation



Transfer learning

- Method extremely useful because it allows to exploit the knowledge of patterns learned with different problem
- Transfer learning uses pre-trained model
- The pre-trained model was trained on a large benchmark dataset
- Pre-trained model in transfer learning are based on Convolutional Neural Network
- In our case we used two models:
 - ResNet
 - VGG

ResNet as feature extractor

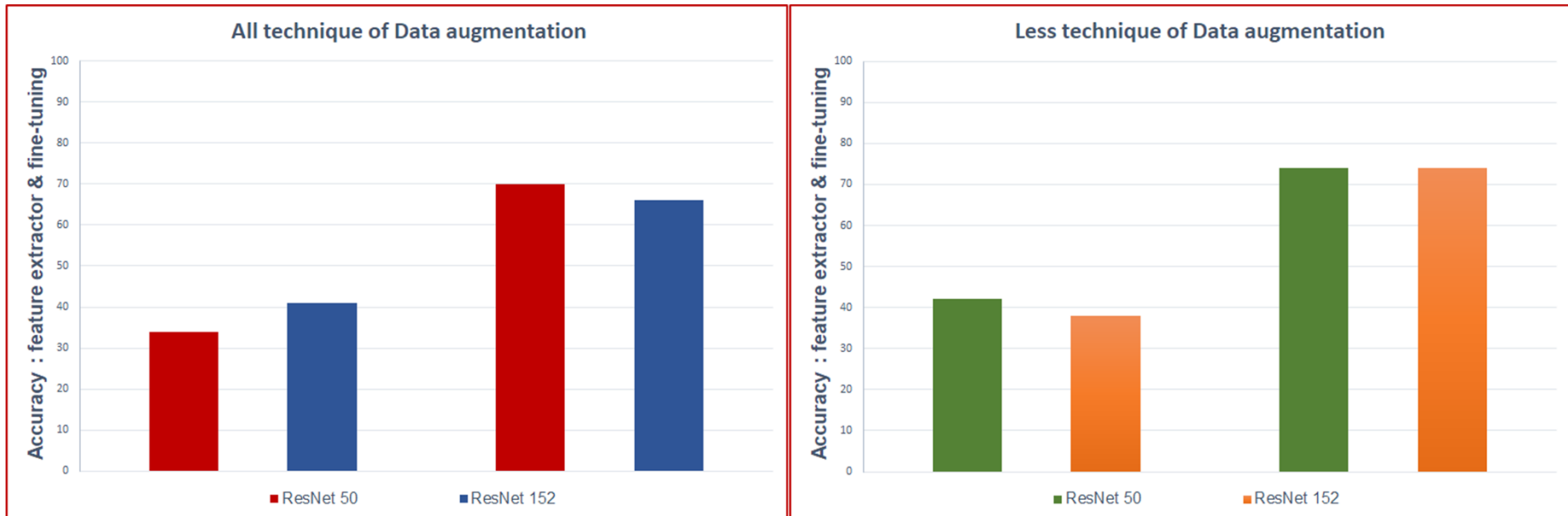
- The Residual Network has a main innovation: the residual module which uses a skip connection. This skip connection exploits the identity paths to connect input and output
- We load ResNet 50 from disk using pre-trained ImageNet weights, without the fully connected layer
- Every ResNet layer is frozen
- Creation of new layers for the prediction
- Training of the latest added layer and evaluation

Fine tuning of ResNet model

- To improve the accuracy we made a fine tuning of the whole model
- Each layer can participate to the transfer learning process:
 - The weights are initialized with the pre-trained neural network model
 - The layers are unfrozen
 - During the training process all weights are updated
- The accuracy is higher because the weights are tuned from a generic feature maps to features associated specifically with our dataset

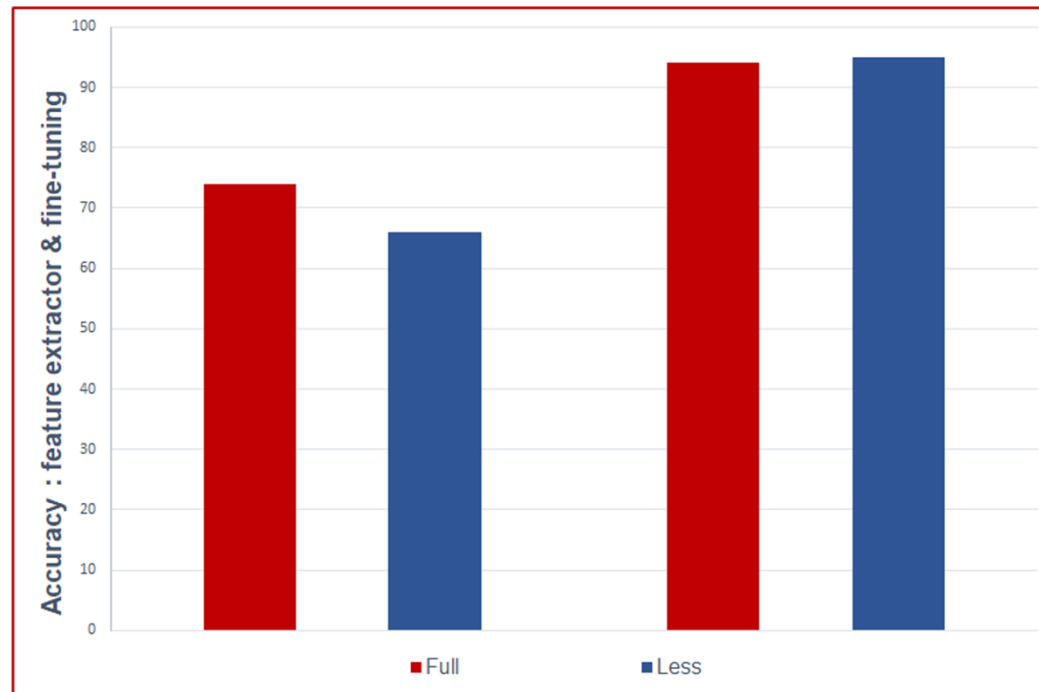
Analyzing ResNet results

- To improve accuracy we also tried ResNet 152



VGG

- Model composed by 19 layers
- Exploit the power of smaller filters and the stack of various 3x3 conv layer
- VGG was used both as feature extractor and with fine-tuning



Conclusions

