Machine Learning Engineer Nanodegree

Capstone Project: Pneumonia detection based on chest X-Ray Images

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I. Definition

Project Overview

Pneumonia is the eighth leading cause of death, and the number 1 cause of death from infectious disease, in the United States. About 1 million adults in the US are hospitalized with pneumonia every year, and about 50,000 die from this disease. Globally, pneumonia is the leading cause of death in children under 5 years old. There are 120 million cases of pneumonia reported each year, and over 10% (14 million) progress to severe episodes. An estimated 935,000 deaths from pneumonia occurred in children under the age of 5 years in 2013.

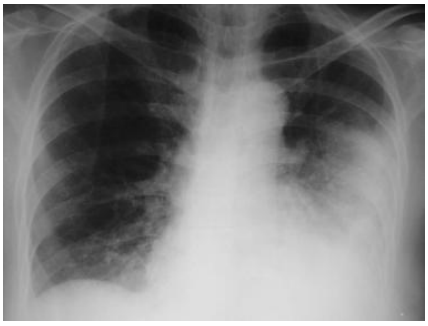


Figure 1 - Image in a 49-year-old woman with pneumococcal pneumonia.

Chest radiography with posteroanterior and lateral views is the preferred imaging examination for the evaluation of typical bacterial pneumonia (Figure 1). The problem of pneumonia detection based on chest X-Ray Images was already tackled in the literature. (Pranav Rajpurkar, 2017) develops an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Their algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. (Parveen NR, 2011) used unsupervised fuzzy c-means classification learning algorithm for the detection of pneumonia infection. (Benjamin Antin, 2017) also followed the approach of CheXNet with a 121-layer dense Convolutional Neural Network (DenseNet).

Problem Statement

This project will try to perform a similar task using deep learning techniques. The problem is a binary classification where the inputs are chest X-ray images and the output is one of two classes: pneumonia or non-pneumonia with a certain confidence. Data on chest X-ray images are provided on Kaggle site (Mooney). This dataset includes more than 5000 images split in two categories: normal and pneumonia. In order to be able to provide such solution, the following strategy is applied:

- Implementation of a CNN model build from scratch
- Optimization of the previous CNN model
    - Dropout layers
    - Data augmentation
- Implementation of a CNN model using transfer learning technique
    - Using the bottleneck features of a pre-trained network
    - fine-tuning the first layers of a pre-trained network
- Implementation of a class activation maps for visualizing where deep learning networks pay attention

The problem comes down to being able to determine if lungs are infected with pneumonia or not and where is located the infected area.

Metrics

The proposed project is based on a two-stage classification of lung analysis: Normal or Pneumonia. By paying attention to the provided dataset on chest X-ray images, it can be seen that the two classes are not well balanced. The accuracy evaluation metric is discarded in order to avoid the accuracy paradox. Therefore, the use of F1 score as a measure of metric evaluation is more accurate than the accuracy measure. F1 score ranges between 0 and 1. It is defined as:

$$F1\ score = \frac{2 * true\ positive}{2 * true\ positive + false\ negative + false\ positive}$$

$$F1\ score = \frac{2 * Recall * Precision}{Recall + Precision}$$

Table 1 - Confusion Matrix

	Predicted class		
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

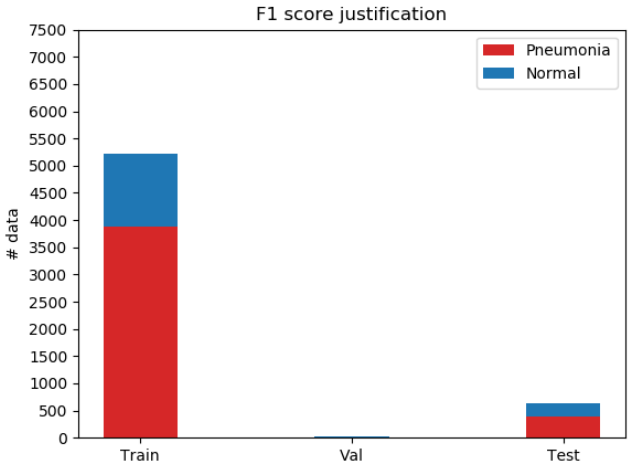
II. Analysis

Data Exploration

The dataset used for this project was provided on Kaggle site and upload by Paul Mooney[1]. This set is already split in three folders and each one is subdivided in two classes:

- Train file (5218 images)
  - Normal (± 25%)
  - Pneumonia (± 75%)
- Val file (9 images)
  - Normal (50%)
  - Pneumonia (50%)
- Test file (624 images)
  - Normal (± 37%)
  - Pneumonia (±63%)

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. F1 is usually more useful than accuracy, especially if you have an uneven class distribution which is true by observing Graph 1:



Graph 1 - F1 score justification

All of the images includes in the dataset are in a gray scale format but with various size. This first analysis, only based on the number of images, the size of the images and the ratio between each classes, gives a clue on which techniques will be required (data augmentation, F1 score and standardization method).

[1] https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia/downloads/chest-xray-pneumonia.zip/2

Exploratory Visualization

In contrast to some datasets, the visualization and extraction of features and properties is quite complex in this case. Only a trained eye, such as a radiologist, is able to recognize and discern any differences between the two images below. On the left image (*Figure 2*), it is the lungs chest X-ray of a patient in good health (not being infected with pneumonia). On the right image (Figure 3), this is the chest X-ray of a patient with pneumonia.

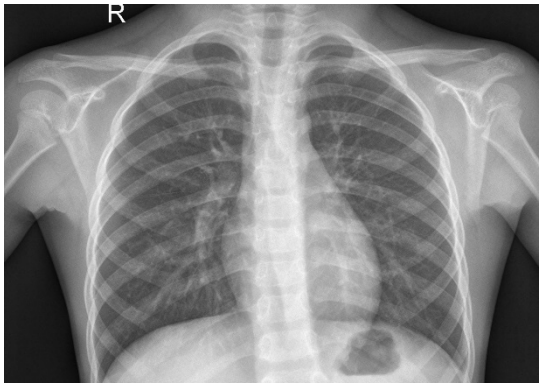


Figure 2 - Patient not infected by pneumonia

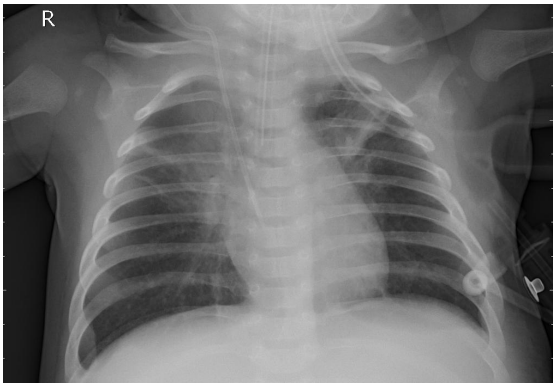


Figure 3 - Patient infected by pneumonia

By analyzing the two images, we understand the importance of implementing deep learning in the medical field. These neural networks are able to detect and recognize patterns that humans cannot detect. Moreover, by showing the potential infected areas, doctors can improve their accuracy. Decision support is therefore increased.

Algorithms and Techniques

Classifiers used here are Convolutional Neural Network, which are the state-of-the-art algorithm for most image processing tasks, including classification. For example, the following parameters can be tuned to optimize the classifier:

- Number of layers
- Layer types (convolutional, fully-connected, or pooling)
- Layer parameters

In order to solve the problem, the following algorithms and techniques are followed. As a starting point, a vanilla CNN was built from scratch in a completely random way. The schematic diagram is drawn in Figure 4. The following parameters for the optimizer were selected:

Table 2 - Parameters for the vanilla model

Optimizer	Loss	Metrics
rmsprop	Binary cross-entropy	F1

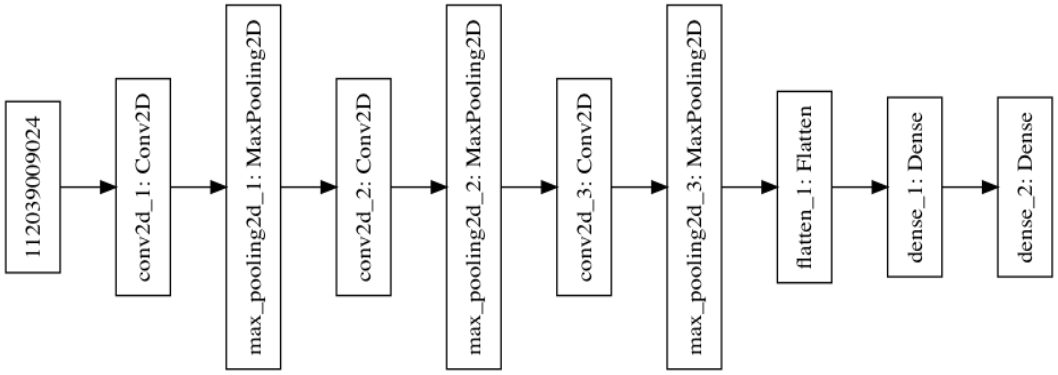


Figure 4 - Schematic diagram of the vanilla CNN

In order to improve the performance obtained with the previous CNN, some dropout layers were added (Figure 5) and others optimizer were tested. Moreover, a number of random transformations (ImageDataGenerator) were applied on the validation set in order to increase the number of data. This helps prevent overfitting and helps the model generalize better.

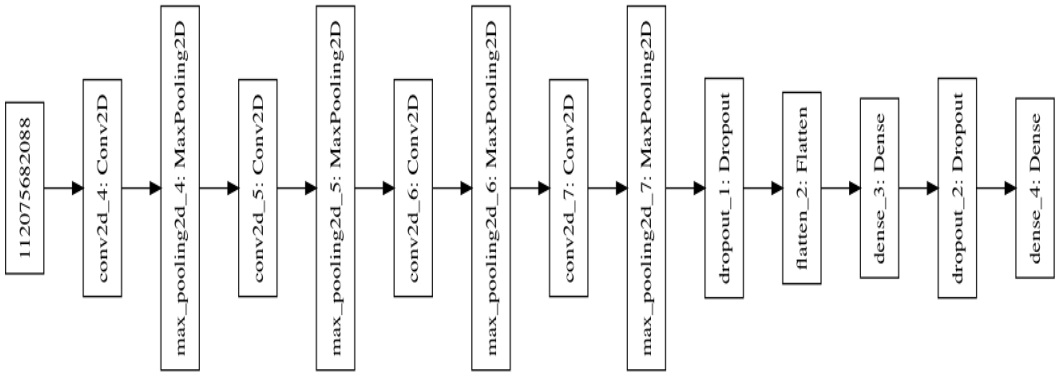


Figure 5 - Schematic diagram of the optimized CNN

The following parameters for the optimizer were selected:

Table 3 - Compilation parameters

Optimizer	**Loss**	**Metrics**
Adam	Binary cross-entropy	F1
SGD	Binary cross-entropy	F1

After that, in this project, the pre-trained Inception-V3 model was selected (Figure 6). Inception-v3 is trained for the ImageNet Large Visual Recognition Challenge using the data from 2012. This is a standard task in computer vision, where models try to classify entire images into 1000 classes, like "Zebra", "Dalmatian", and "Dishwasher". Because the dataset of this project is completely different from Inception-V3 one, the bottleneck features of a pre-trained network is used and then the fine-tuning of the first layers was performed as suggested in Table 4.

Table 4 - Transfer learning justification

	Similar dataset	Different dataset
Small dataset	Transfer learning: highest level features + classifier	Transfer learning: lower level features + classifier
Large dataset	Fine-tune*	Fine-tune*

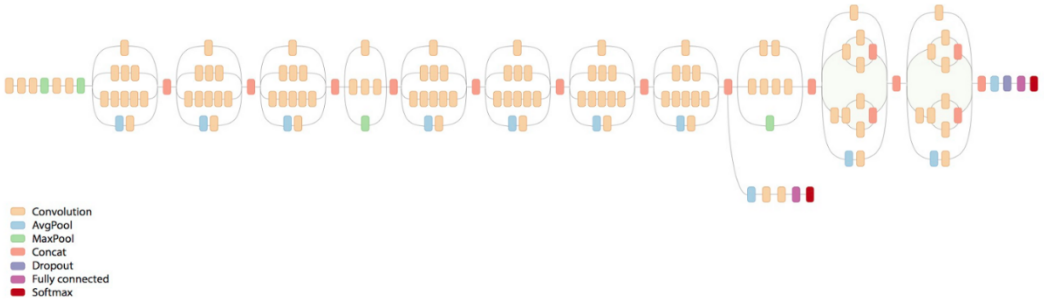


Figure 6 - Schematic diagram of Inception V3

Finally, a Class Activation Maps was implemented to get the discriminative image regions used by a CNN to identify a specific class in the image. A class activation map (CAM) let see which regions in the image were relevant to this class.

Benchmark

By definition the benchmark acts as a threshold that can determine if the project has succeeded or not. The F1 value returned with the vanilla CNN model will be used as a reference. Any performance of improvement will lead to a higher score than the benchmark model. With the vanilla CNN model, the F1 score is 0.625.

III. Methodology

Data Preprocessing

To preprocess the data, the following steps were followed:

- The data were already divided in three folders when downloaded it directly on the Kaggle site (train, val and test folder)
- Each of the three folders was subdivided in two other folders: NORMAL and PNEUMONIA.
- flow_from_directory() automatically infers the labels from the directory structure of the folders containing images. Every subfolder inside the training-folder(or validation-folder) was considered a target class (Figure 7).

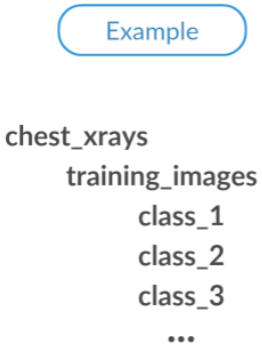


Figure 7 - Label extraction

- To prevent overfitting, data augmentation was performed using ImageDataGenerator () with the followings parameters:
    - rotation_range is a value in degrees (0-180), a range within which to randomly rotate pictures
    - width_shift and height_shift are ranges (as a fraction of total width or height) within which to randomly translate pictures vertically or horizontally
    - rescale is a value by which we will multiply the data before any other processing. Our original images consist in RGB coefficients in the 0-255, but such values would be too high for our models to process (given a typical learning rate), so we target values between 0 and 1 instead by scaling with a 1/255. factor.
    - shear_range is for randomly applying shearing transformations
    - zoom_range is for randomly zooming inside pictures
    - horizontal_flip is for randomly flipping half of the images horizontally -- relevant when there are no assumptions of horizontal assymetry (e.g. real-world pictures).
    - fill_mode is the strategy used for filling in newly created pixels, which can appear after a rotation or a width/height shift.

Implementation

The project was coded in Python on the Jupyter Notebook plateform. The required libraries used in this project are:

- numpy
- keras
- TensorFlow as backend
- sklearn
- tqdm
- PIL
- import_ipynb
- matplotlib
- cv2

In the initial implementation, a few variables through the use of the load_files function from the scikit-learn library was used to obtain arrays containing file paths to images and arrays containing onehot-encoded classification labels.
The Pneumonia detection based on chest X-Ray Images problem was solved using two different methods and approaches.
In a first step, once the optimization of CNN architecture model was achieved by adding some dropout layers and performing the data augmentation, the variable criterion was the selection of the appropriate optimizer. Randomly, two optimizers were tested: the 'Adam' optimizer et the 'Stochastic Gradient Descent'.
Adam optimizer is an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments.
Stochastic Gradient Descent optimizer is an algorithm that addresses both of the issues (computing cost and no easy way to incorporate new data in an 'online' setting) by following the negative gradient of the objective after seeing only a single or a few training examples.
In a second step, during the transfer Learning method it was decided to test only one optimizers. Only the number of layers trained/layers freezed changed during the evaluation of the model performance. All of the codes of this project can be found on a Github repository[2].

Finally, one big challenge was the use of the F1 score with Keras. Indeed, according to the Keras 2 release notes: « Several legacy metric functions have been removed, namely matthews_correlation, precision, recall, fbeta_score, fmeasure. » A sample code to compute and print out the f1 score, recall, and precision at the end of each epoch, using the whole validation data is available in the Annex.

Refinement

The process of improvement made is reported in Table 5 and Graph 4 where it can be observed how the computation decreases compare to the benchmark model. The same observation can be done by comparing the F1 score between different techniques.

[2] https://github.com/FrancoisMasson1990/Machine_Learming_Engineer_Nanodegree_Program/tree/master/Capstone_Final_Francois

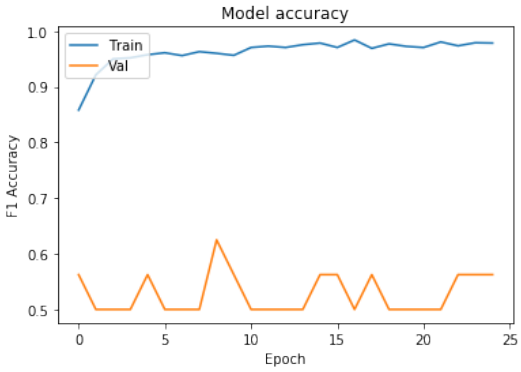
IV. Results

Model Evaluation and Validation

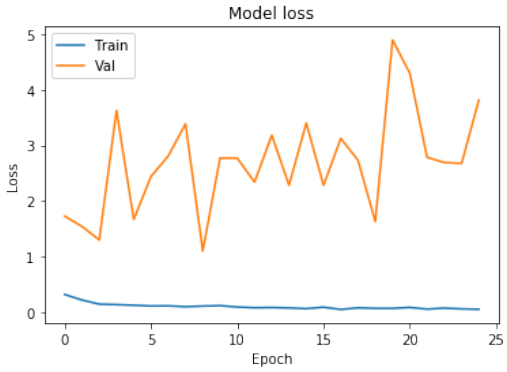
During development, a validation set was used to evaluate the model. The final architecture and hyperparameters were chosen because they performed the best among the tried combinations. Here is a list of every parameters used in optimized CNN architecture model:

- The shape of the filters of the convolutional layers is 2*2.
- The first convolutional layer learns 16 filters, the second learns 32 filters, the third one learns 64 filters and the fourth one learns 16 filters.
- The paddings were defined as same.
- The convolutional layers have a stride of 2, so the resolution of the output matrices is half the resolution of the input matrices.
- The pooling layers have a size of 2. The last pooling layers has a size of 4.
- The first fully connected layer has 500 outputs, the second 2. (The outputs of the latter correspond to the two classes, “Normal” and “Pneumonia”).
- Two dropout layers were needed (0.2 and 0.4) in order to reduce the overfitting parameters.
- The Relu activation function was selected on intermediate layers. For the last one layer, the softmax function was implemented.

Graph 2 and 3 shows that even on a small number of epochs, the F1 score quickly reach out a plateau for the train set and the loss tends towards an asymptotic value.



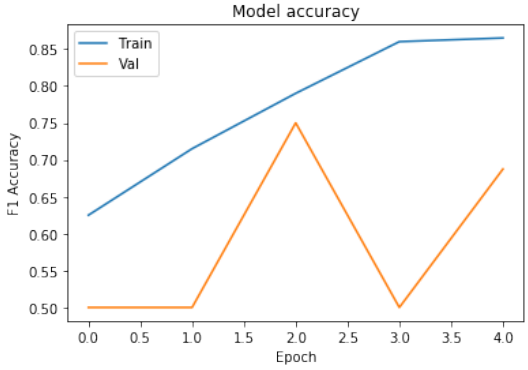
Graph 2 - F1 accuracy evolution



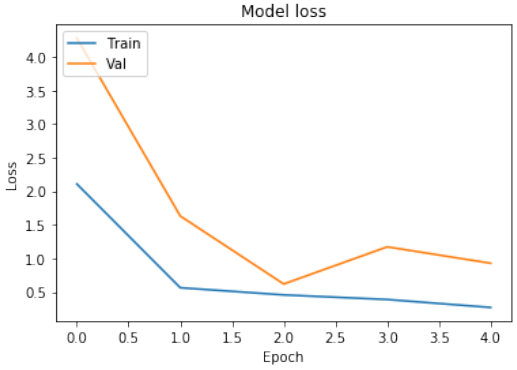
Graph 3 - Loss evolution

Even If this model provided the highest F1 score (0.831), the learning curves show overfitting as there is a big gap between train and validation data (Graph 2 and Graph 3).

At the opposite, the Inception-V3 pre-trained model only got a F1 score of 0.713 but the learning curves follows the same pattern. It can be concluded that the overfitting is reduced here. (Graph 4 and Graph 5)



Graph 4 – F1 accuracy evolution



Graph 5 - Loss evolution

To verify the robustness of the final model, a test was conducted by implementing a class activation maps on a test sample with the optimized CNN model with Adam (Figure 8 and 9) and the Inception-V3 pre-trained (Figure 10 and 11). We get sharper visualization with the Inception-V3 pretrained than with the other algorithm.

Class activation maps with the optimized CNN model with Adam:

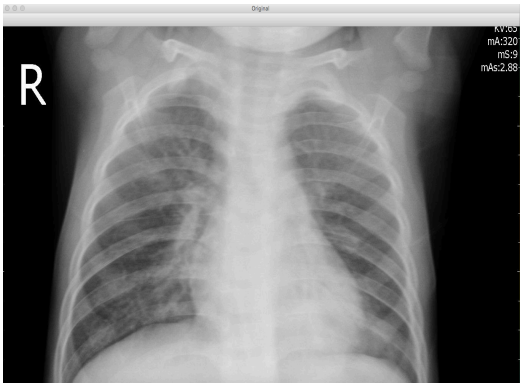


Figure 8 - Infected lungs

Figure 9 - class activation maps predictions

Class activation maps with the Inception-V3 pre-trained model:

Figure 10 - Infected lungs

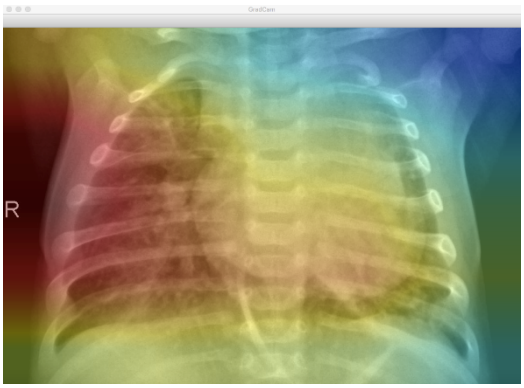


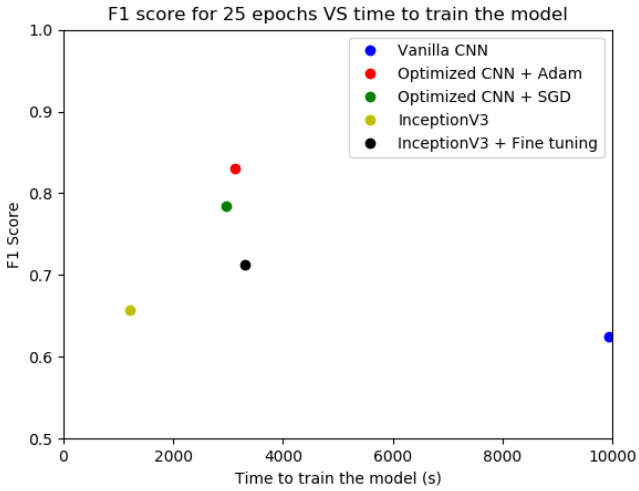
Figure 11 - class activation maps predictions

Justification

The model's solution and its results are compared to the benchmark previously established on Table 5 and Graph 6. The F1 score value significantly increased in the case of the optimized CNN model architecture with the adam optimizer but led to overfitting in the validation data as explained before. The computation time is also quiet acceptable knowing that only a CPU (Intel HD Graphics 5000 1536 Mo) was used. It is also interesting to note that the transfer learning combined with fine-tuning is a powerful technique. By only train the first layers and freeze the rest of them, the F1 score increases from 0.657 to 0.713.

Table 5 - F1 scores

	F1 score on test set
Vanilla CNN with adam optimizer	0.625
Optimized CNN with adam optimizer	0.831
Optimized CNN with SGD optimizer	0.785
Inception-V3 pre-trained model	0.657
Inception-V3 pre-trained model + fine tuning	0.713



Graph 6 - F1 score vs computation time

V. Conclusion

Free-Form Visualization

As mentioned earlier, the visualization and extraction of patterns is crucial in this project. Having an algorithm that can predict with some confidence the probability of being infected is crucial but it becomes even more efficient if the algorithm is able to show and to determine the suspected area of the disease. That's why the implementation of a class activation maps for visualizing where deep learning networks pay attention is a powerful tool. On the left image (*Figure 12*), it is the chest X-ray of a patient infected by the pneumonia. On the right image (Figure 13), the heat map highlights some region of interest detected by the algorithms. That can be a good starting for doctors to know where to look at.

Figure 12 - Infected lungs

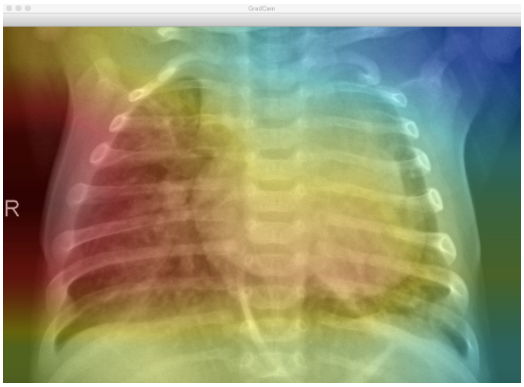


Figure 13 - class activation maps predictions

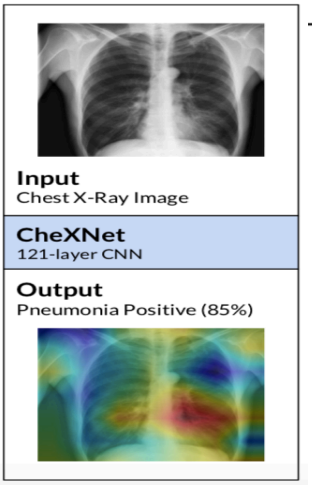
Reflection

The goal of this project was to find a way to correctly and with some accuracy recognize lungs infected by the pneumonia. To achieve this, various CNN model architectures were tested. Starting from a vanilla model, the accuracy was improved by using some dropout layers to the original model. Techniques such as data augmentation, tuning on hyperparameters and selection on various optimizers were tested as well. The objective was to obtain the highest evaluation score as possible. Because of the non-balanced classes issue, the F1 score was selected. Finally, a good compromise between the computed time and the F1 score was found. One very interesting aspect of this project was to see how a machine learning technique with a model trained on one task (cats and dogs recognition) is re-purposed on a second related task (pneumonia detection). One difficult aspect of this project was to find a way to visualize how well the algorithms performed. Some intensives researches were needed before discovering the class activation maps technique.

Improvement

The problem itself is quite simple and binary. It is also very easy to imagine that the model could be improved by using more available data. Choosing to train the program on a GPU instead of a CPU could drastically decrease the computation time as well allowing more complex CNN architecture. The last layers could also be split in more than just two classes to detect others lung disease. As an example, Standford researcher created a 121-layer convolutional neural network (CheXNet) trained on ChestX-ray14, currently the largest publicly available chest X- ray dataset, containing over 100,000 frontal-view X-ray images

with 14 diseases. As provided below, they get an accuracy 76% for detecting pneumonia in infected lungs.



CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Pathology	Wang et al. (2017)	Yao et al. (2017)	CheXNet (ours)
Atelectasis	0.716	0.772	**0.8094**
Cardiomegaly	0.807	0.904	**0.9248**
Effusion	0.784	0.859	**0.8638**
Infiltration	0.609	0.695	**0.7345**
Mass	0.706	0.792	**0.8676**
Nodule	0.671	0.717	**0.7802**
Pneumonia	0.633	0.713	**0.7680**
Pneumothorax	0.806	0.841	**0.8887**
Consolidation	0.708	0.788	**0.7901**
Edema	0.835	0.882	**0.8878**
Emphysema	0.815	0.829	**0.9371**
Fibrosis	0.769	0.767	**0.8047**
Pleural Thickening	0.708	0.765	**0.8062**
Hernia	0.767	0.914	**0.9164**

VI. References

Benjamin Antin Joshua Kravitz, Emil Martayan Detecting Pneumonia in Chest X-Rays with Supervised [Revue]. - 2017.

Mooney Paul [En ligne]. - https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

Parveen NR Sathik MM Detection of Pneumonia in chest X-ray images. [Revue]. - 2011.

Pranav Rajpurkar Jeremy Irvin, Kaylie Zhu, and Co CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays [Revue]. - 2017.

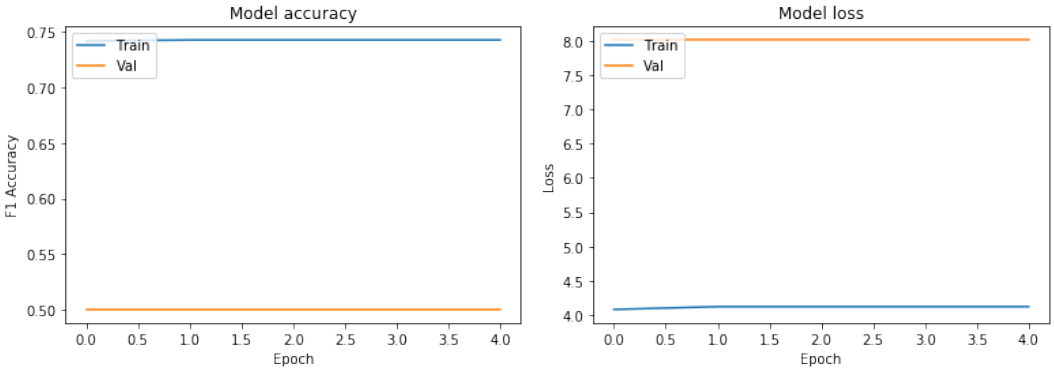
VII. Annex

F1 score implementation

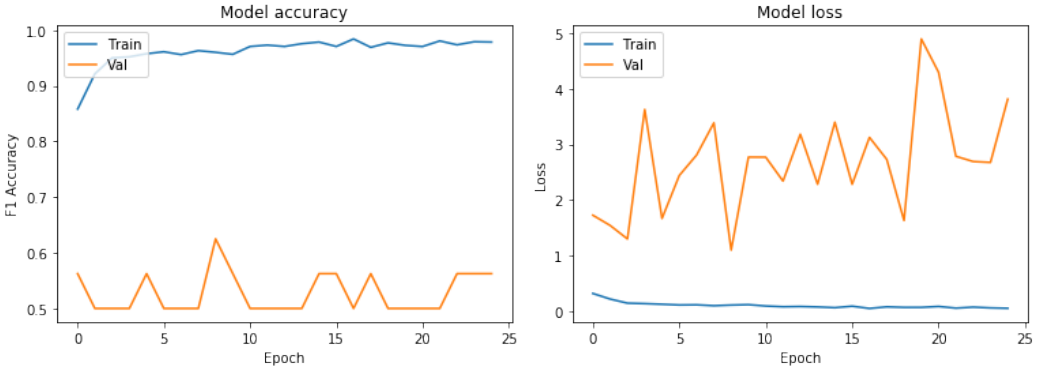
```
from keras import backend as K

def f1(y_true, y_pred):
    def recall(y_true, y_pred):
        """Recall metric.

        Only computes a batch-wise average of recall.

        Computes the recall, a metric for multi-label classification of
        how many relevant items are selected.
        """
        true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
        possible_positives = K.sum(K.round(K.clip(y_true, 0, 1)))
        recall = true_positives / (possible_positives + K.epsilon())
        return recall

    def precision(y_true, y_pred):
        """Precision metric.

        Only computes a batch-wise average of precision.

        Computes the precision, a metric for multi-label classification of
        how many selected items are relevant.
        """
        true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
        predicted_positives = K.sum(K.round(K.clip(y_pred, 0, 1)))
        precision = true_positives / (predicted_positives + K.epsilon())
        return precision
    precision = precision(y_true, y_pred)
    recall = recall(y_true, y_pred)
    return 2*((precision*recall)/(precision+recall+K.epsilon()))
```

Plot of the training and validation losses

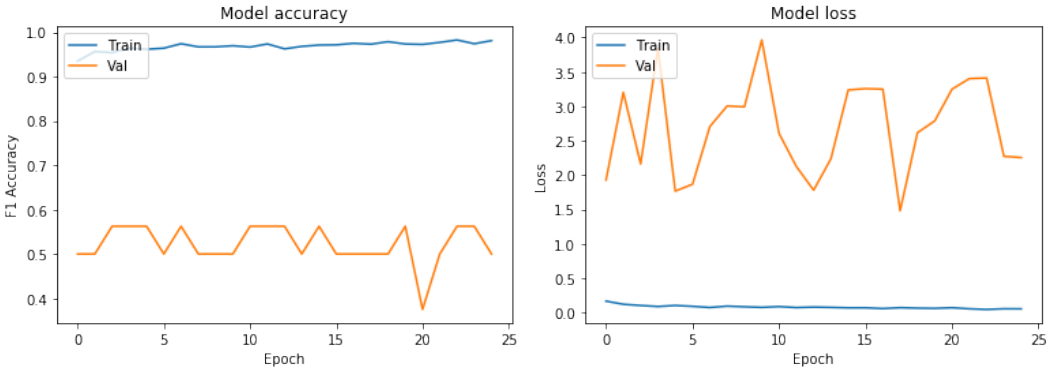
Vanilla CNN with adam optimizer



Optimized CNN with adam optimizer



Optimized CNN with SGD optimizer



Inception-V3 pre-trained model