# SCREENING X-RAY IMAGES FOR COVID-19 INFECTIONS

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# TASK

**Goal :** understand if a patient has a COVID-19 infection
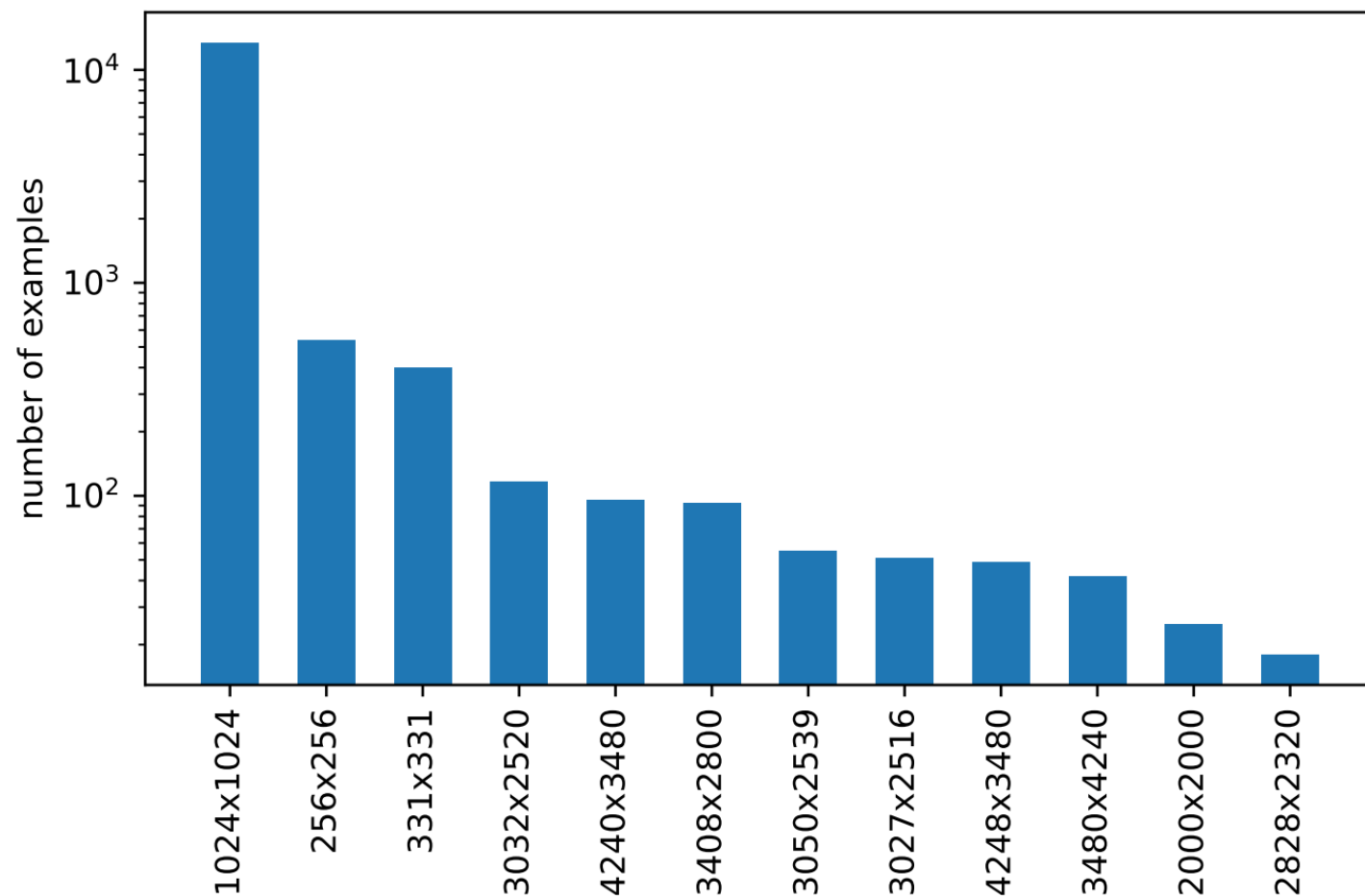
**Data :** X-ray image of the chest

**Task :** binary classification task with an unbalanced dataset

# DATASET

| | Train Set | Test Set |
|---|---|---|
| Positive | 2,158 (14%) | 200 (50%) |
| Negative | 13,793 (86%) | 200 (50%) |
| **Total** | 15,951 | 400 |

The COVIDx CXR-2 dataset

# DATASET



The dataset is not uniform in terms of size of the images.

All the images are resized to 224x224

# PREPROCESSING

Before training, the images are preprocessed.

Since some images contain writings on the upper part, the images are cropped (8% of the top-part)

# PREPROCESSING

We are interested only on the chest, so we center crop the image to remove useless parts
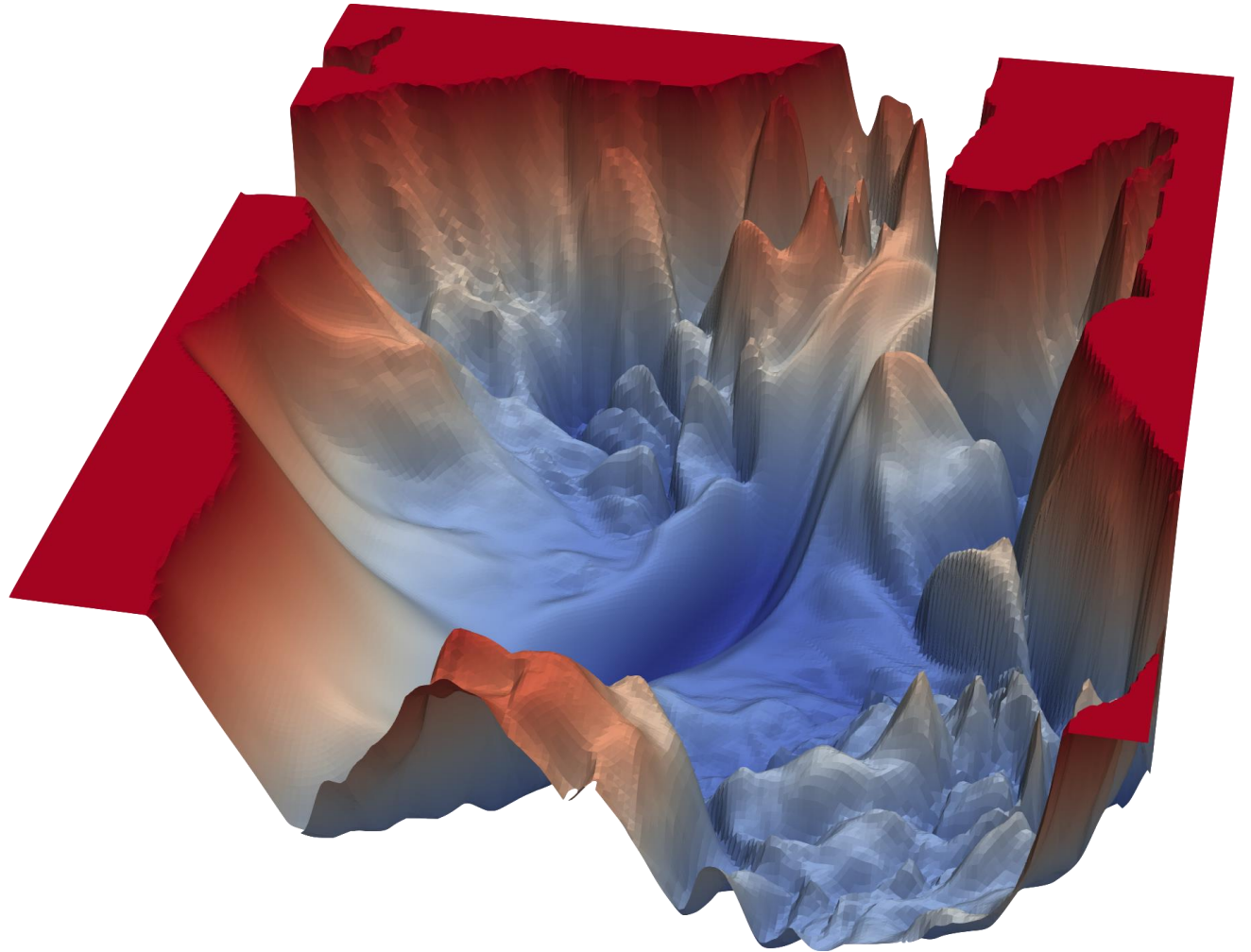
# PREPROCESSING

We investigated the use of histogram-equalization to enhance the quality of the images
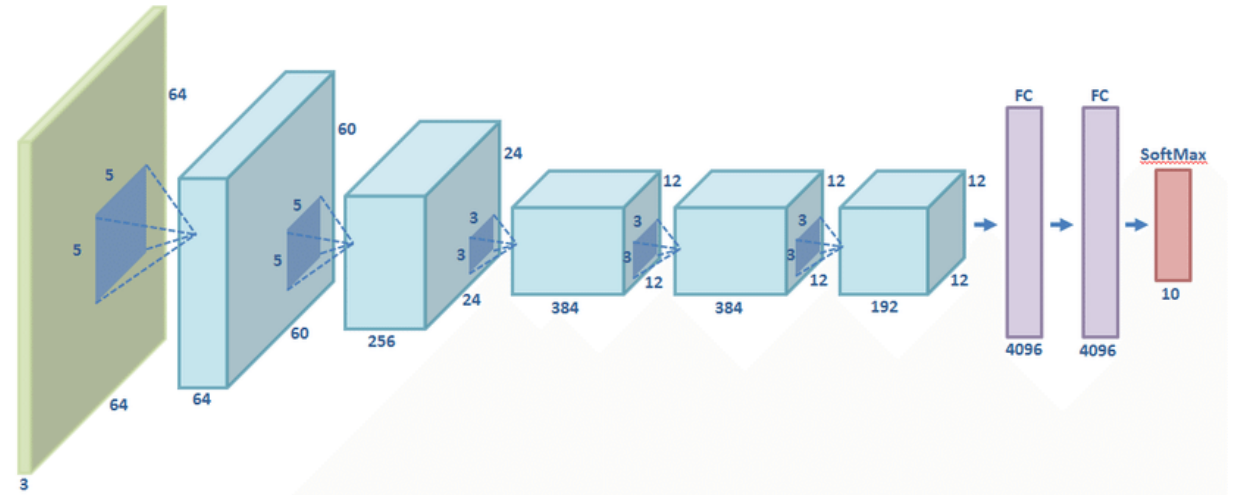
# NEURAL NETWORKS

- AlexNet
- VGG16
- ResNet50
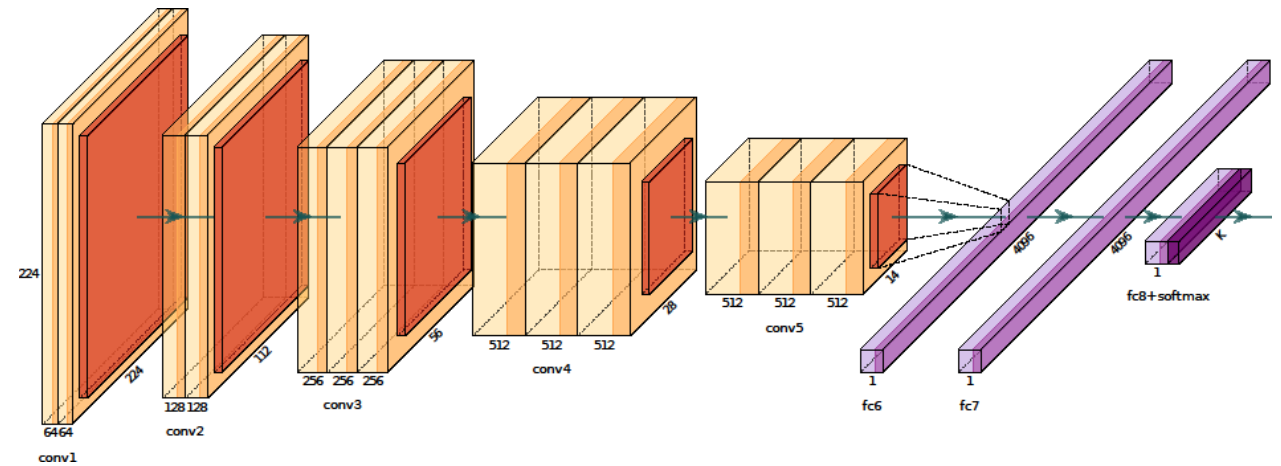- DenseNet121
- InceptionV3

# NEURAL NETWORKS

AlexNet:

- convolutional neural network (CNN)
- no skip connections
- ReLU activation functions
- dropout

# NEURAL NETWORKS

VGG:

- convolutional neural network (CNN)
- stacks of 3x3 and 1x1 convolutions
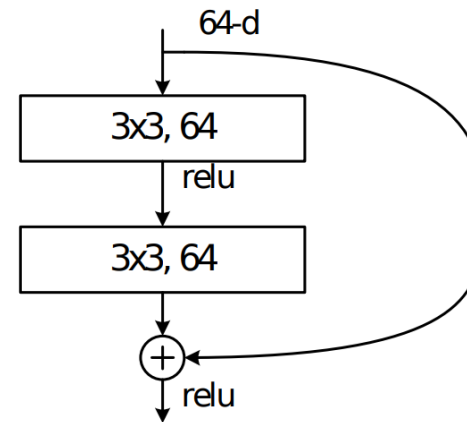- ReLU activation functions

# NEURAL NETWORKS

ResNet:

- convolutional neural network (CNN)
- skip-connections
- residual convolutional blocks (basic/bottleneck)
- improves convergence rate → higher learning rate
- batch normalization

Basic block

64-d

3x3, 64
relu

3x3, 64

⊕
relu

Bottleneck block

256-d

1x1, 64
relu

3x3, 64
relu

1x1, 256

⊕
relu
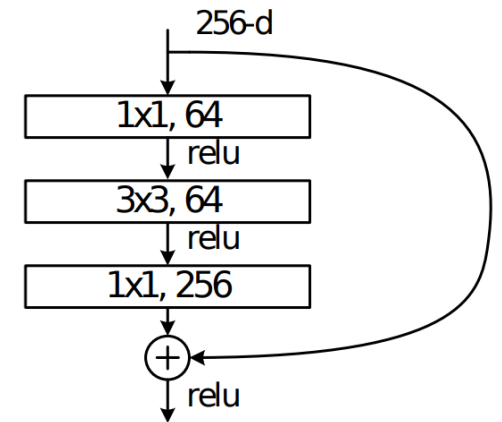
# NEURAL NETWORKS

DenseNet:
- convolutional neural network (CNN)
- direct connections to all subsequent layers (dense block)
- transition layers (convolution and pooling)
- ReLU activation functions
- batch normalization
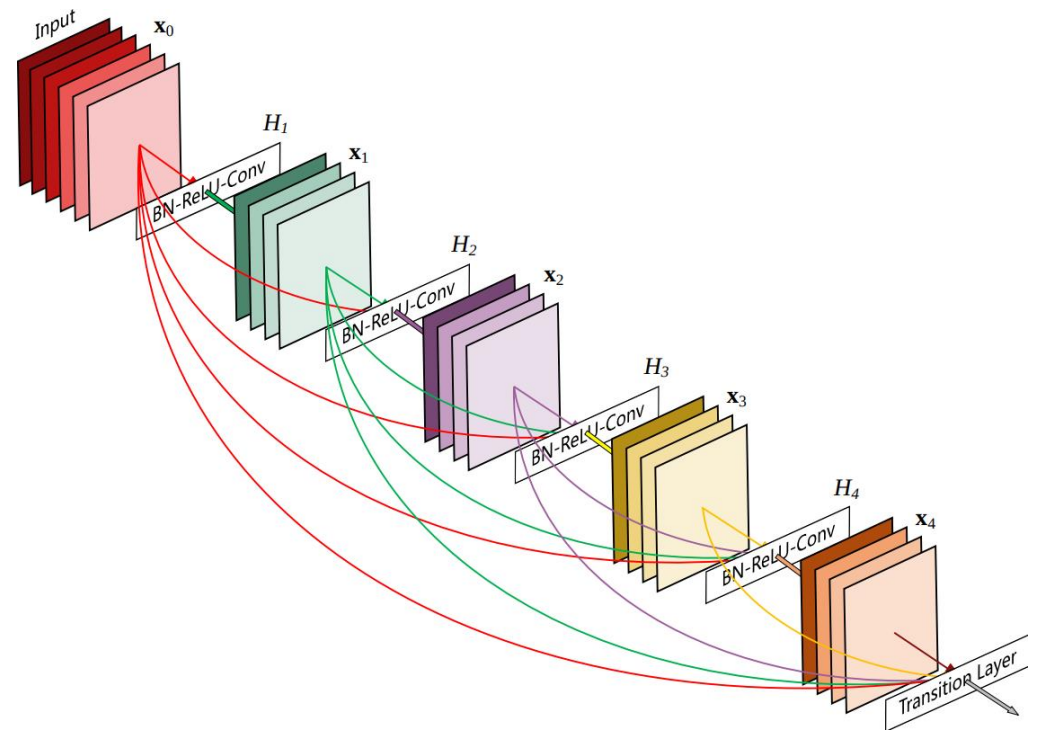
# NEURAL NETWORKS

InceptionV3:
- convolutional neural network (CNN)
- inception modules (parallel convolutions)
- auxiliary classifiers
- factorized convolutions
- ReLU activation functions
- batch normalization



InceptionV3 block
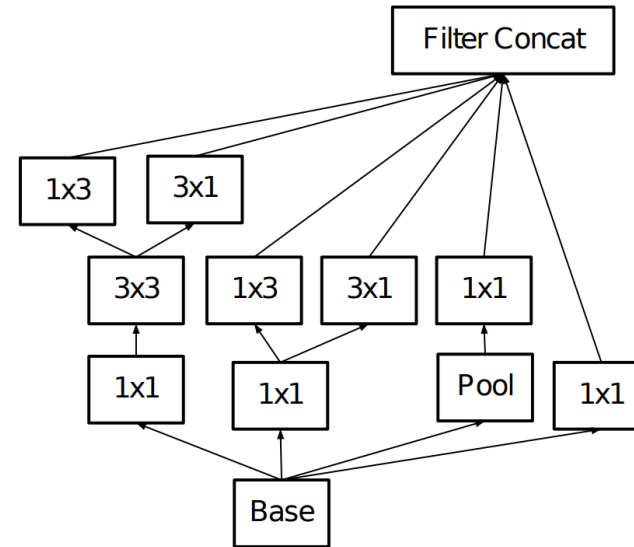
InceptionV1 block
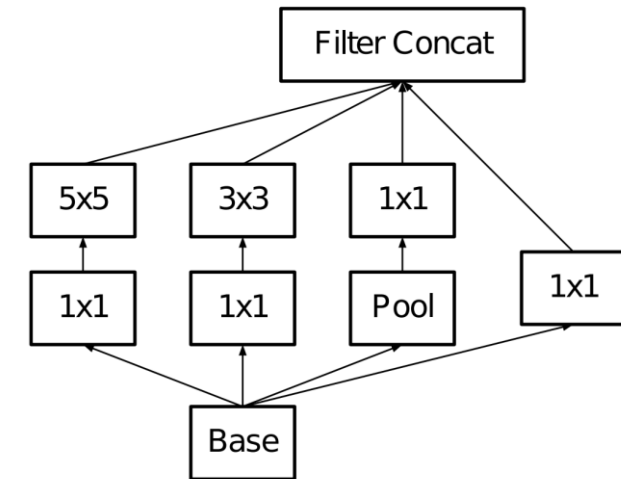
# METHODOLOGY

- Data augmentation
  - random scaling (10%)
  - random translation (10%)
  - random rotation (10°)
  - histogram-equalization (optional)

- Adam optimizer
  - learning rate $1 \times 10^{-4}$ for AlexNet and VGG16
  - learning rate $1 \times 10^{-3}$ for the others

# METHODOLOGY

- Note for InceptionV3
  - input size 299x299
  - auxiliary classifier with cross-entropy loss weighted by a factor of 0.3
- Batch size 32
- No L2 regularization
- 100 epochs with early stopping (20 patience)
- Binary cross entropy weighted by taking into account dataset unbalance.

# TOOLS AND HARDWARE

- Python 3.9
- PyTorch library
- GoogleColab
- Nvidia GTX-1660
- Intel 4460 quad-core 3.4 GHz

# EVALUATION

| Architecture | With Histogram Equalization | | | Without Histogram Equalization | | |
| --- | --- | --- | --- | --- | --- | --- |
| | Precision | Recall | F1 | Precision | Recall | F1 |
| AlexNet | 0.918 | 0.905 | 0.904 | 0.932 | 0.923 | 0.922 |
| VGG16 | 0.890 | 0.863 | 0.860 | 0.876 | 0.835 | 0.830 |
| ResNet50 | **0.953** | **0.952** | **0.952** | **0.949** | **0.945** | **0.945** |
| DenseNet121 | **0.955** | **0.955** | **0.955** | 0.919 | 0.905 | 0.904 |
| InceptionV3 | 0.933 | 0.925 | 0.925 | **0.975** | **0.975** | **0.975** |

Metrics are macro averaged over the two classes

# EVALUATION

| Architecture | # params (M) | CPU Time (ms) | GPU Time (ms) |
|---|---|---|---|
| AlexNet | 57.0 | 21.5 | 2.6 |
| VGG16 | 134.3 | 171.0 | 12.7 |
| ResNet50 | 23.5 | 95.1 | 11.0 |
| DenseNet121 | 7.0 | 84.1 | 21.5 |
| InceptionV3 | 21.8 | 116.4 | 18.3 |

Number of parameters and inference time for each model

# EVALUATION

| Architecture | Input size | Precision | Recall | Accuracy |
|---|---|---|---|---|
| ResNet50 | 224 x 224 | 0.941 | 0.965 | 0.952 |
| DenseNet121 | 224 x 224 | 0.955 | 0.955 | 0.955 |
| InceptionV3 | 299 x 299 | 0.975 | 0.975 | 0.975 |
| COVID-Net CXR-2 | 480 x 480 | 0.970 | 0.955 | 0.963 |

Comparison with state of the art

# EVALUATION

| Architecture | # params (M) | Inference Time |
|---|---:|---:|
| ResNet50 | 23.5 | 11.0 |
| DenseNet121 | 7.0 | 21.5 |
| InceptionV3 | 21.8 | 18.3 |
| COVID-Net CXR-2 | 8.8 | 71.1 |

Comparison with state of the art

# FUTURE WORK

- Explore more sophisticated preprocessing algorithm to further enhance images


- Explainability and predictions visualization

# REFERENCES

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# GRAZIE PER L'ATTENZIONE