UNIVERSIDAD YACHAY TECH

Pre-processing and Handling Unbalanced Data in CNN for Improving Automated Detection of COVID-19 Cases: Preliminary Results

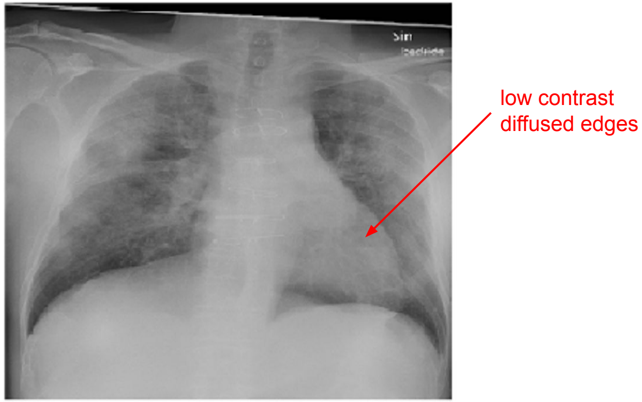
Outline

1. **Motivation**
2. Methodology
3. Results
4. Conclusions

Motivation

- Most covid patients develop visible symptoms in their lungs.
- Deep learning as a powerful tool for processing medical images.
- X rays images are cheap, fast.
- System can be portable.

Non covid-19 chest xray



Covid-19 patterns present in xray

Problems

- Deep learning is promising technique for automatic diagnostic, but it needs huge amounts of data to be generalizable.
- Training sets are not widely available.
- COVID-19-caused pneumonia patterns are diffuse in x-rays.
- Data unbalance.
- Current dataset has not a standard method of acquisition.

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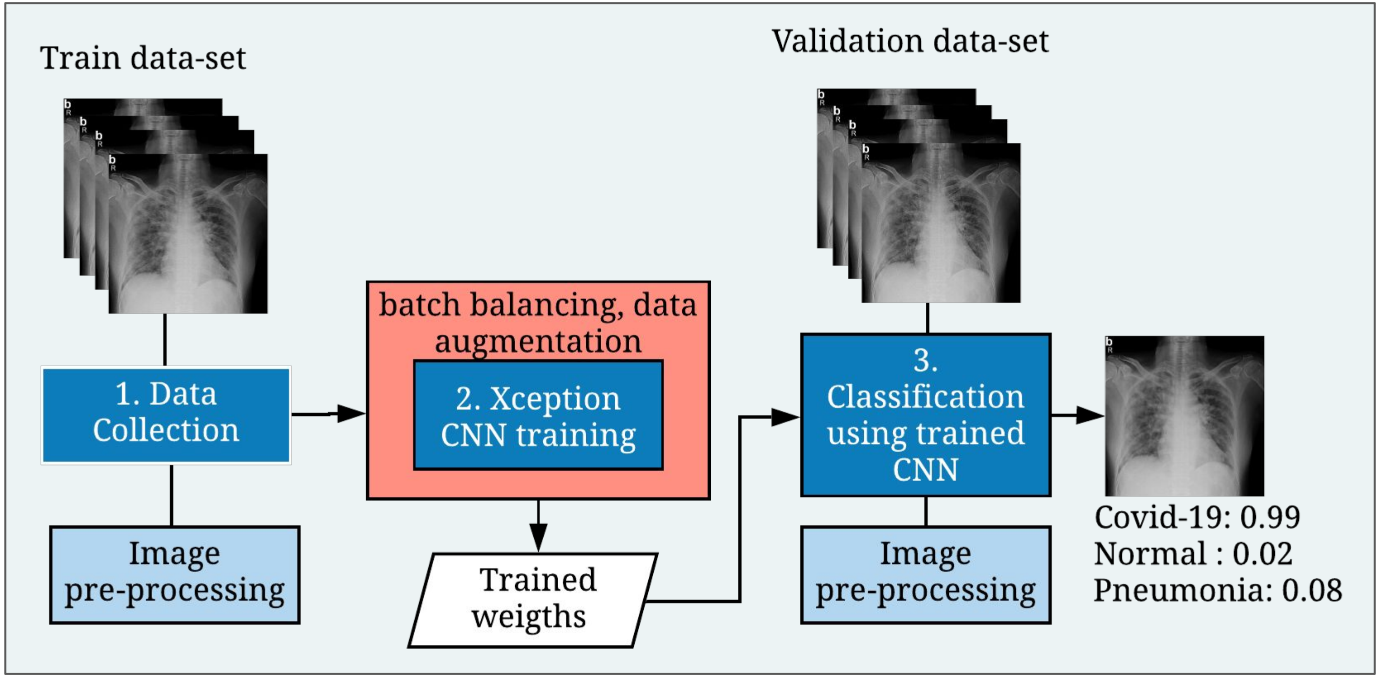
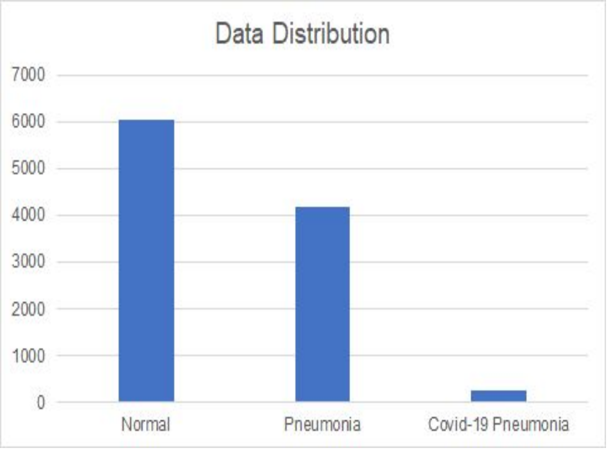
Methodology



System architecture.

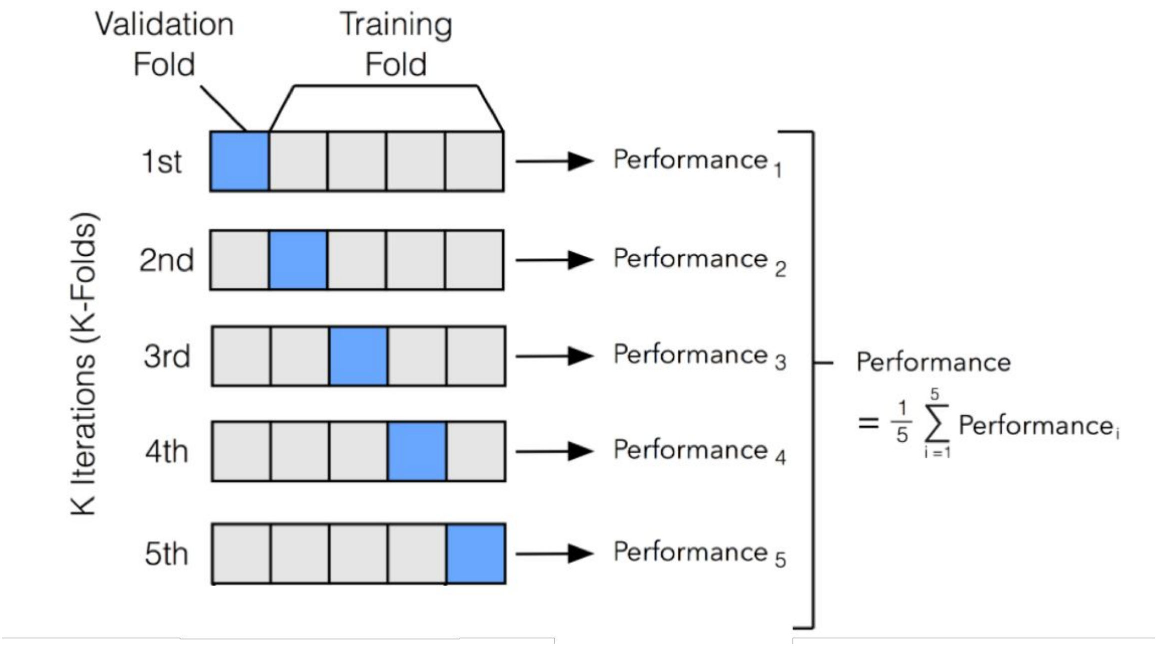
Methodology: Data Collection



Type	Normal	Pneumonia	COVID-19 penumonia	Total
Train	6049	4163	268	10479
Test	2017	1388	90	3495

Data distribution for each fold. Taken from COVIDx dataset [1].

Methodology: Five Fold Cross Validation



Methodology: Unsharp masking pre-processing

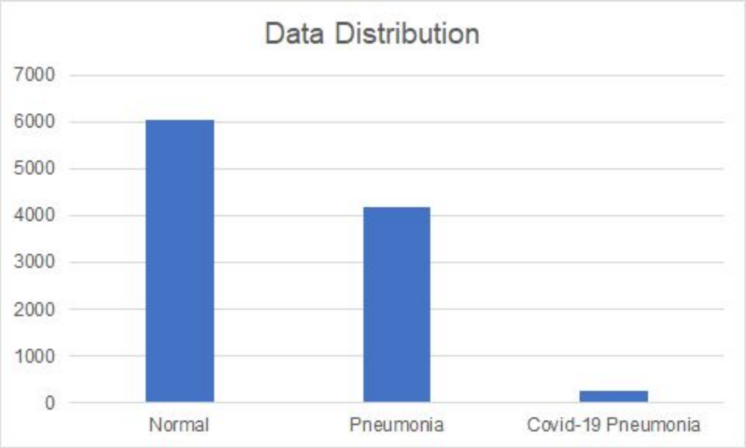
Enhances the visual quality of an image by separating the edges, amplify, and sum them back into the image.

- Gaussian Blur

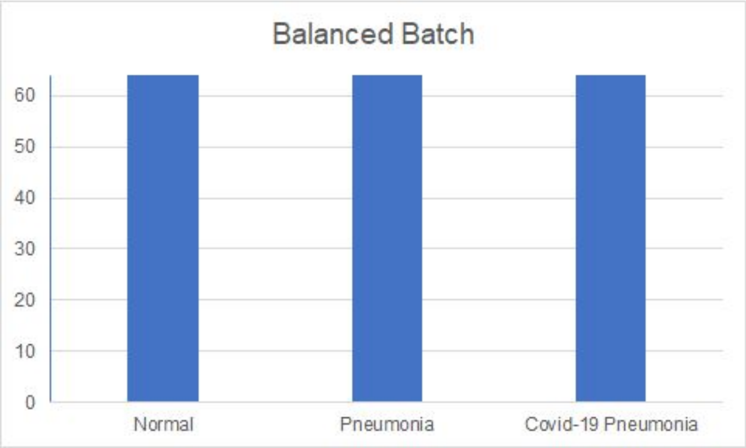
A weighted sum of the result is performed.

$$UM = 1.5\ original - 0.5\ blurred \tag{1}$$

Methodology: Batch balancing



Distribution of the training data.

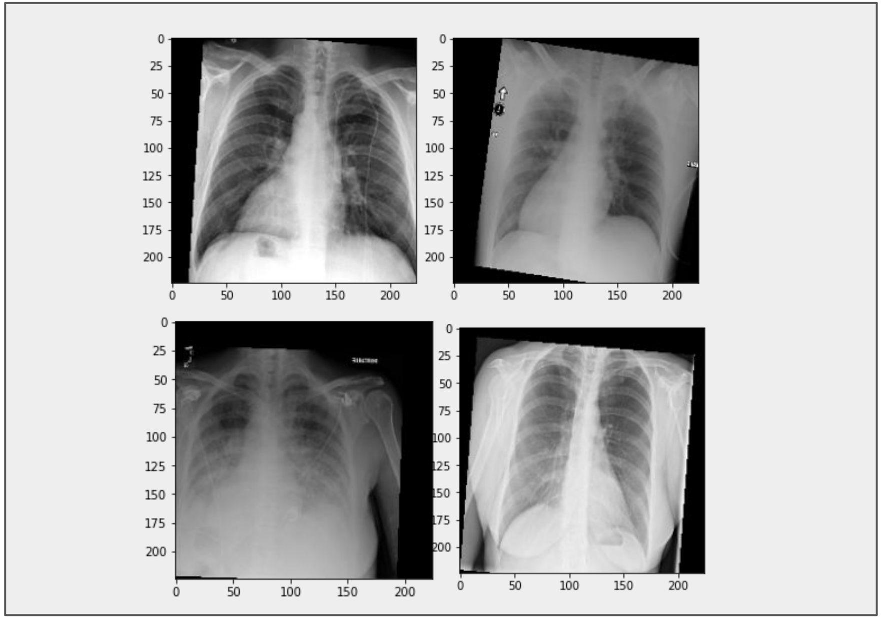


Representation of a balanced batch.

Methodology: Data augmentation

Transformation	Value
rotation	(-10°,10°)
width shift	(-10%,10%)
height shift	(-10%,10)
Horizontal flip	True
Brightness	(85%,115%)

Augmentation parameters.



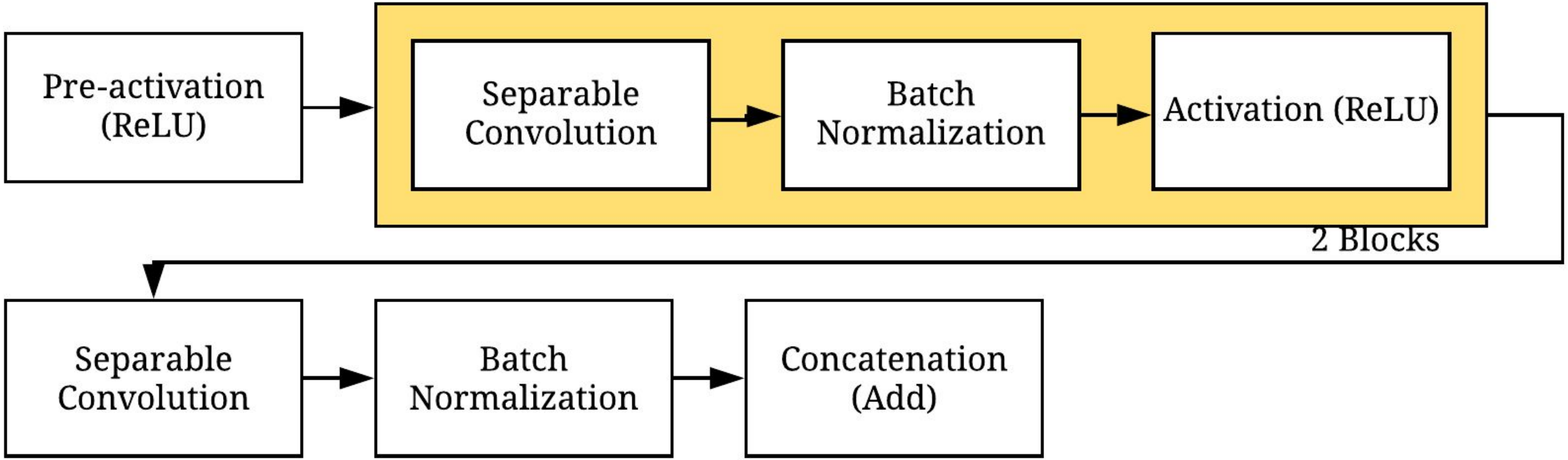
Example of augmented images.

Experimental setup:
Definition of experiments

Experiment	Description
RNB	Raw images, no balancing
RB	Raw images with balance correction
EINB	Enhanced images, no balance correction
EIB	Enhanced images, balance correction

Definition of experiments.

Methodology: Xception CNN architecture



Xception CNN architecture [2].

Experimental setup:
Grid search hyper-parameter optimization

Hyper-parameter	Value space	Description
batch size	[32,**64**,70]	Samples per training iteration
epochs	[10,15,**20**,25,30]	Number of passes over the whole dataset
Image size	[(112,112,3), **(224,224,3)**]	Image dimensions, channels included
Learning rate	[0.0005,0.0001,0.01,0.005,0.001, **0.005 to 0.001 with exp. decay**]	limits the weight update against gradients
Optimizer	**Adam**, SGD	Optimization algorithm

Hyper-parameter space with selected parameters for training in highlighted in blue.

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Results: Qualitative

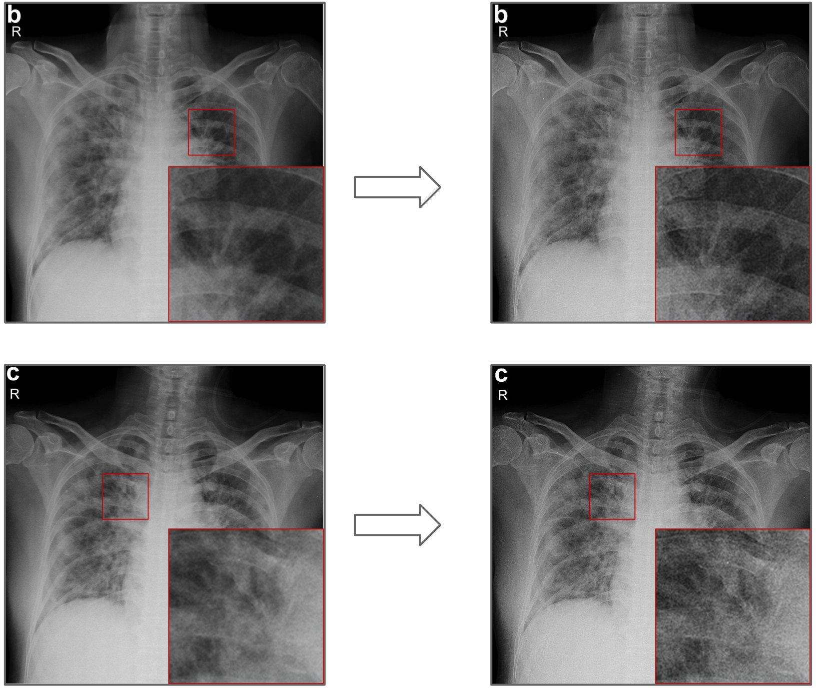


Fig. 8. Original images (left) enhanced edges (right).

Experimental setup: metrics

- **Accuracy:** Is a metric that generally describes how the model performs across all classes. It is calculated as the ratio between the number of correct predictions to the total number of predictions.

$$Accuracy = \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}}$$

- **Precision:** This metric measures the model's accuracy in classifying a sample as positive.

$$Precision = \frac{True_{positive}}{True_{positive} + False_{positive}}$$

- **Recall:** The recall measures the model's ability to detect Positive samples. The higher the recall, the more positive samples detected.

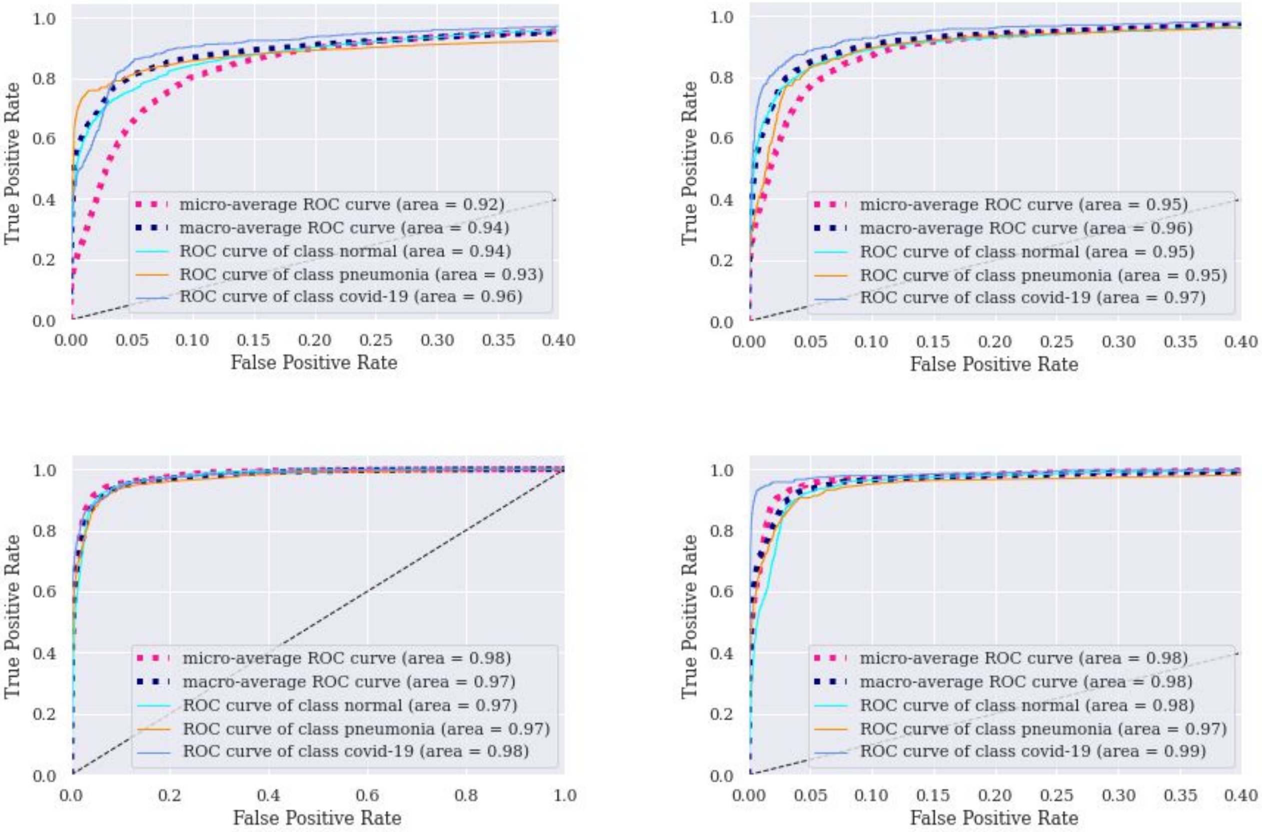
$$Recall = \frac{True_{positive}}{True_{positive} + False_{negative}}$$

Results: Precision, Recall, Accuracy

Class	metric	Experiment				
		RNB	RB	IENB	IEB	COVID-net
Normal	Precision	91.8	93.8	93.4	93.4	90.5
	Recall	88.0	95.4	91.6	95.2	95.0
Pneumonia	Precision	95.4	93.2	89.8	92.0	91.3
	Recall	83.4	90.0	87.8	89.8	94.0
Covid-19	Precision	55.4	82.2	75.0	88.0	98.9
	Recall	85.6	84.4	76.0	80.0	91.0
All	Accuracy	85.2	92.8	89.8	92.8	93.3

Table of results for all experiments and COVID-net as reported in [2].

Results: ROC curves



ROC curves for (a) Raw and imbalanced image samples on training, (b)Raw, balanced image samples, (c) Enhanced, but imbalanced image samples, (d)Enhanced and balanced image samples.

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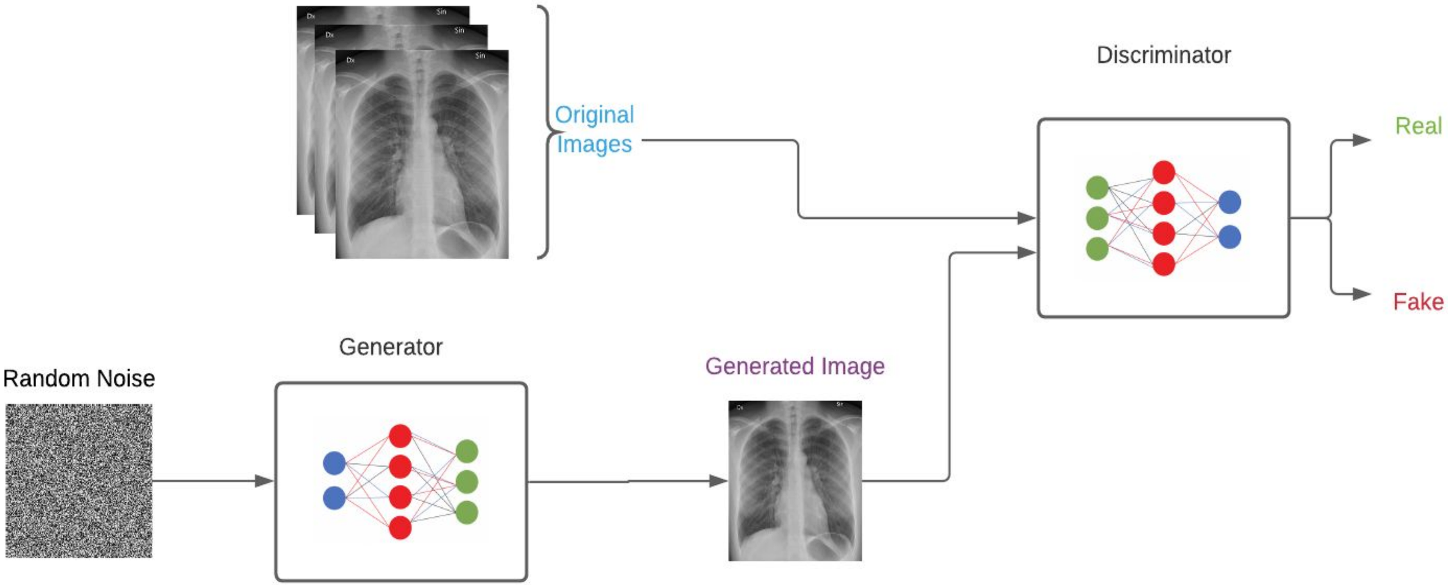
Conclusions

- As a proof of concept, the optimal classifier presented good results, more studies should be performed to determine that the model indeed can be used for medical diagnosis.
- Xception-based models that implemented batch balancing and pre-processing performed better than those that did not.
- Current augmentation method does not introduce new patterns on images and new techniques capable of generating new synthetic images should be visited (Ex. GAN)

Future Work: GAN



Representation of a GAN [3] used for COVID19 chest x-rays.

References

[1] Chollet, F.: Xception: Deep Learning with Depthwise Separable Convolu-tions (oct 2016), http://arxiv.org/abs/1610.02357

[2] Wang, L., Wong, A.: Covid-net: A tailored deep convolutional neural net-work design for detection of covid-19 cases from chest radiography images(2020)

[3] Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434 (2015).

Thank you! For your attention.

Any Questions?