

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

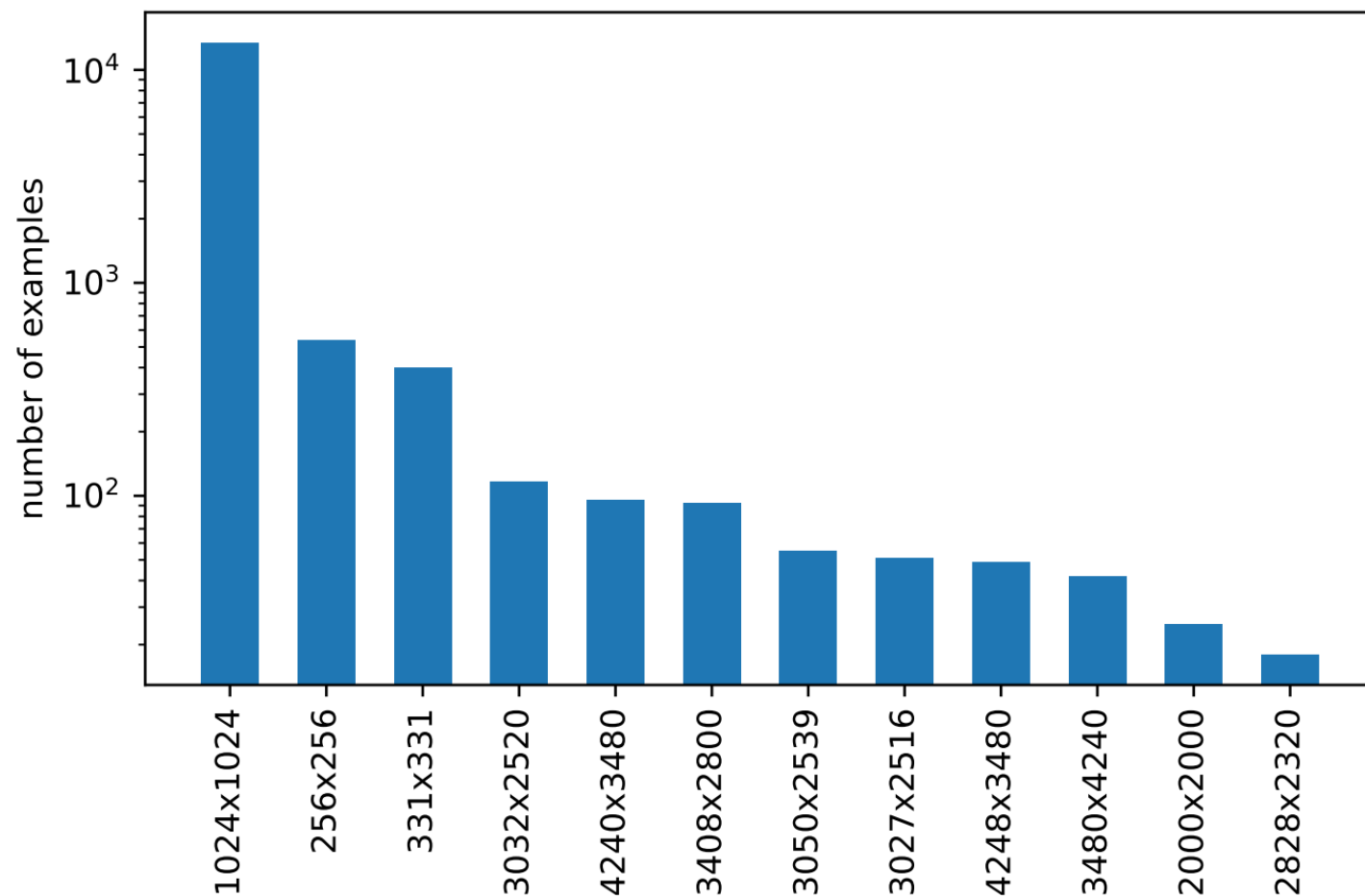
Task : binary classification task with an unbalanced dataset

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

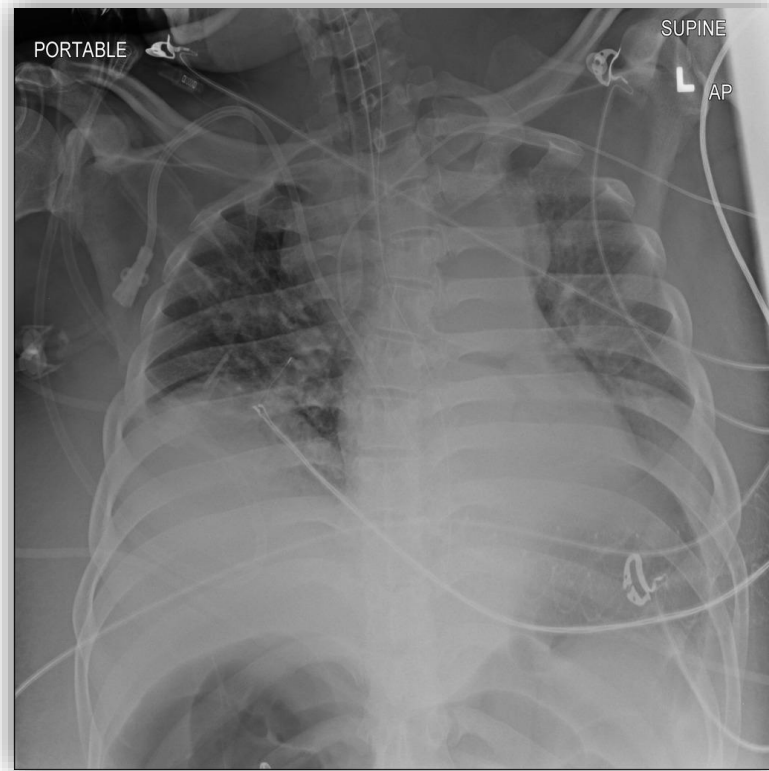
Before training, the images are preprocessed.

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



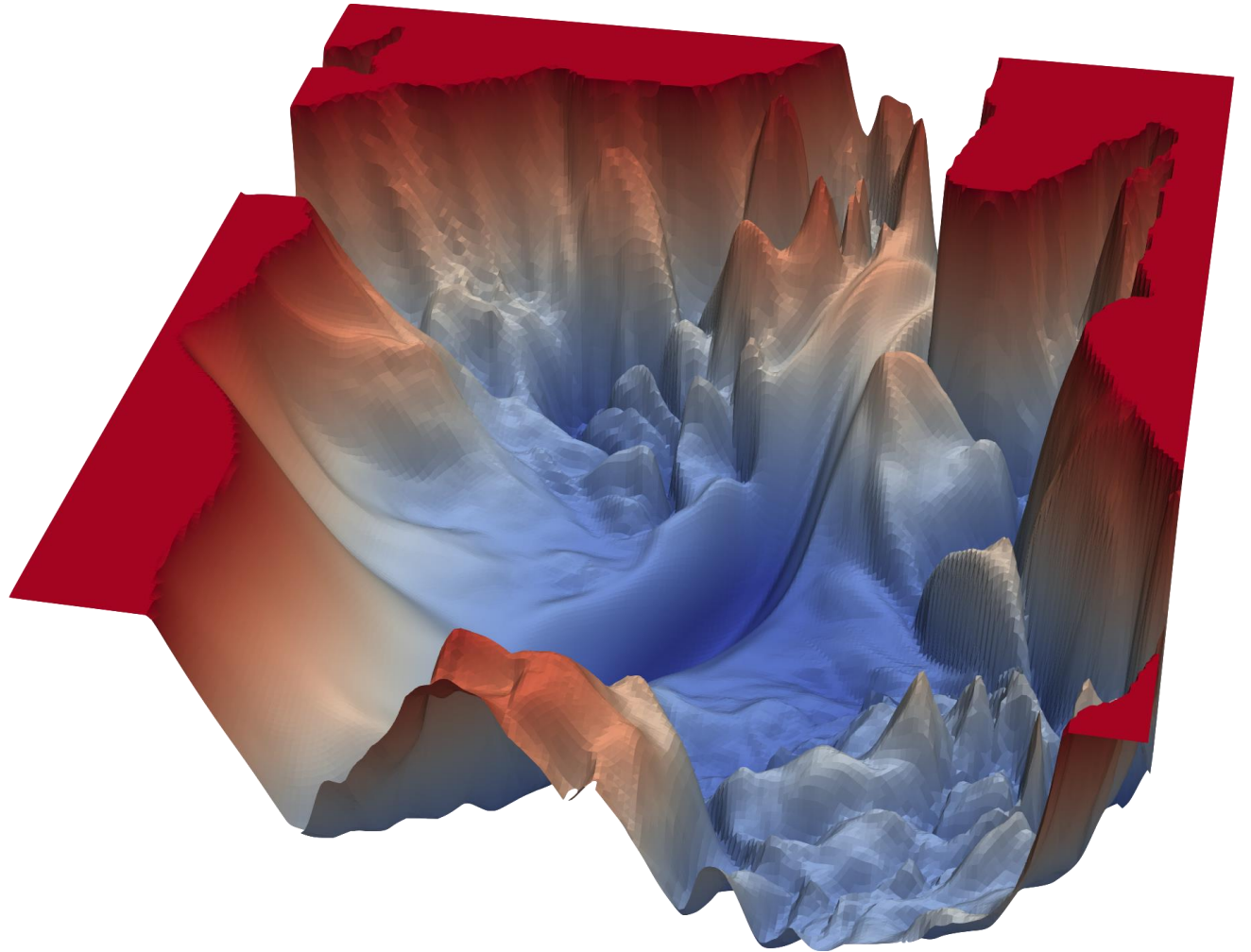
PREPROCESSING

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



NEURAL NETWORKS

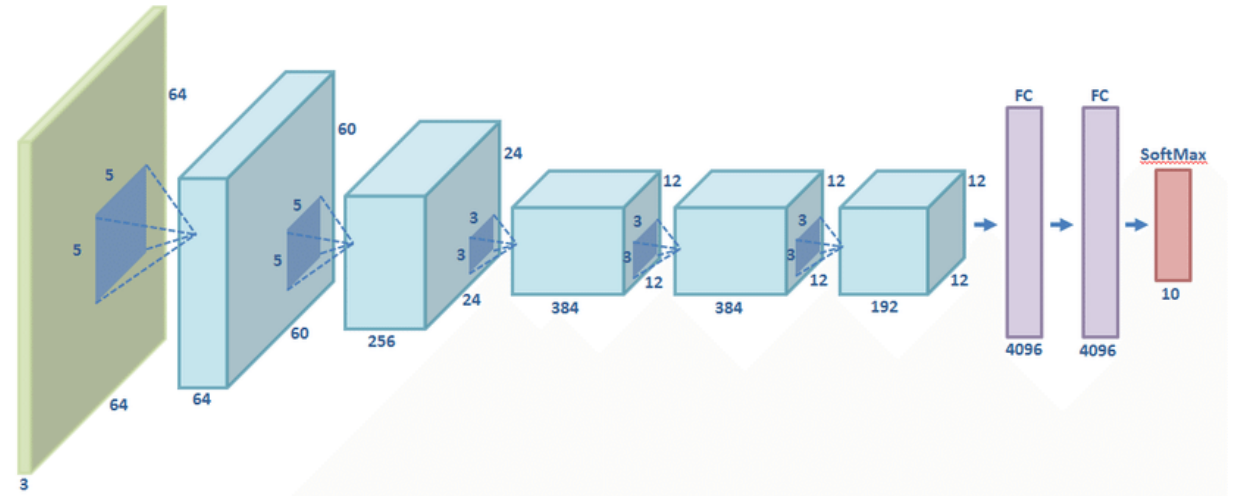
- AlexNet
- VGG16
- ResNet50
- DenseNet121
- InceptionV3



NEURAL NETWORKS

AlexNet:

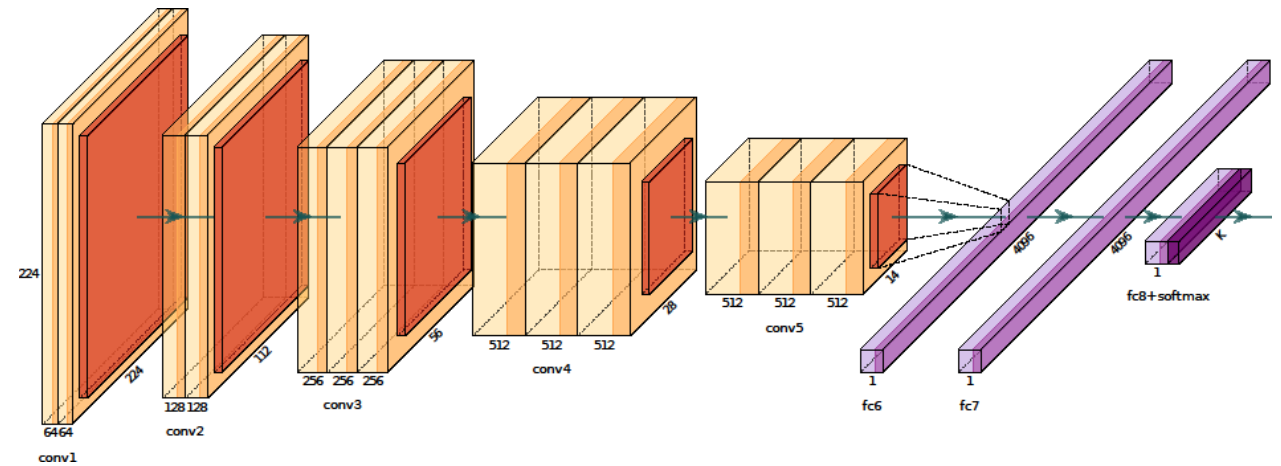
- convolutional neural network (CNN)
- no skip connections
- ReLU activation functions
- dropout



NEURAL NETWORKS

VGG:

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

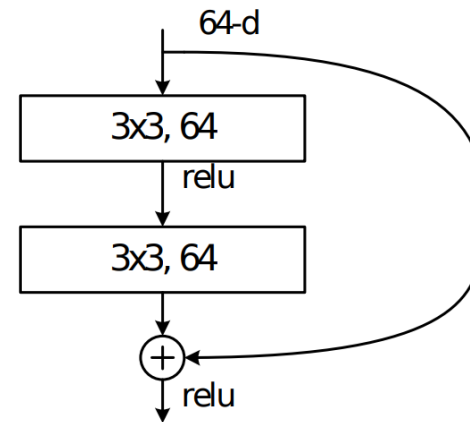


NEURAL NETWORKS

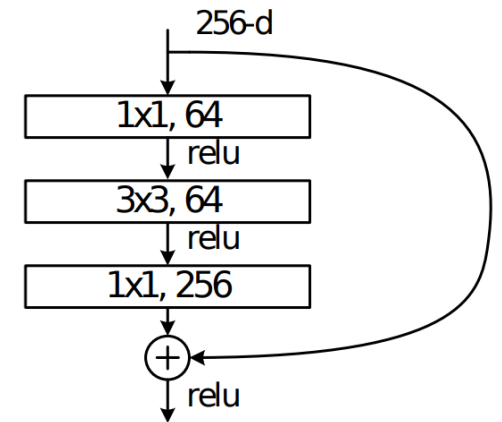
ResNet:

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

Basic block



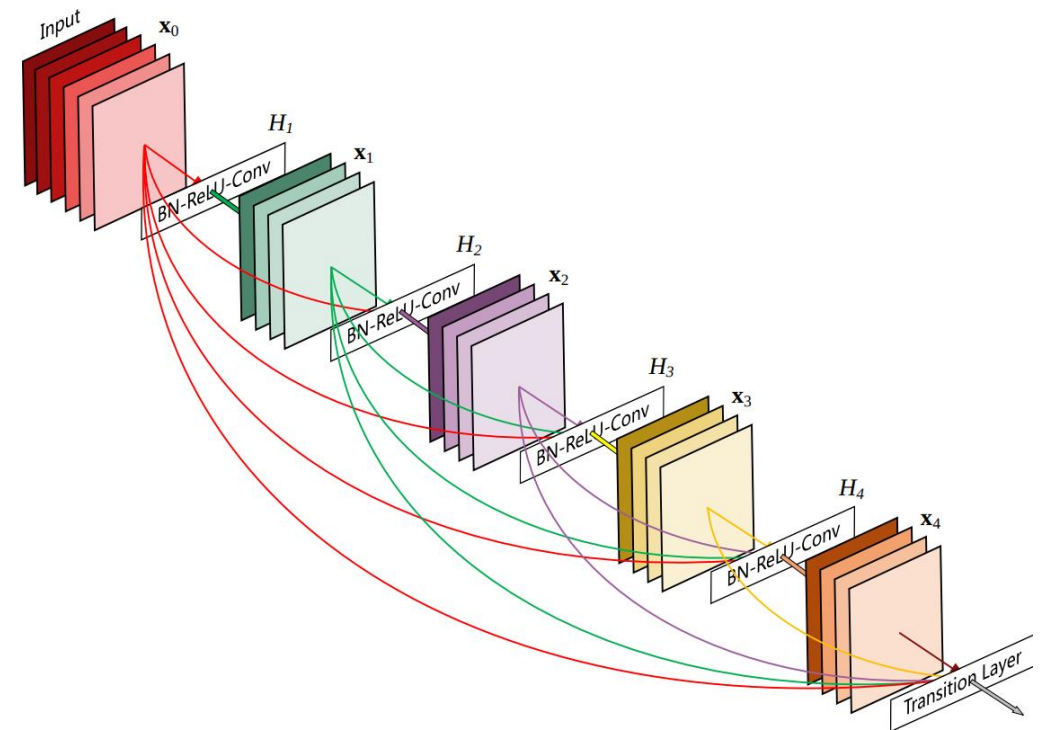
Bottleneck block



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

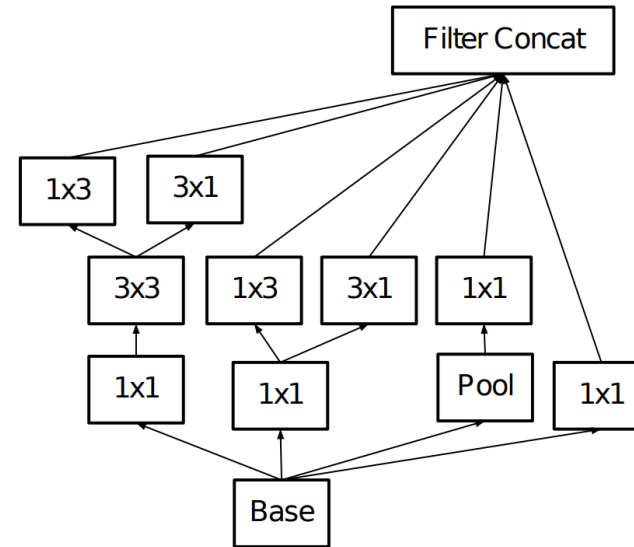


NEURAL NETWORKS

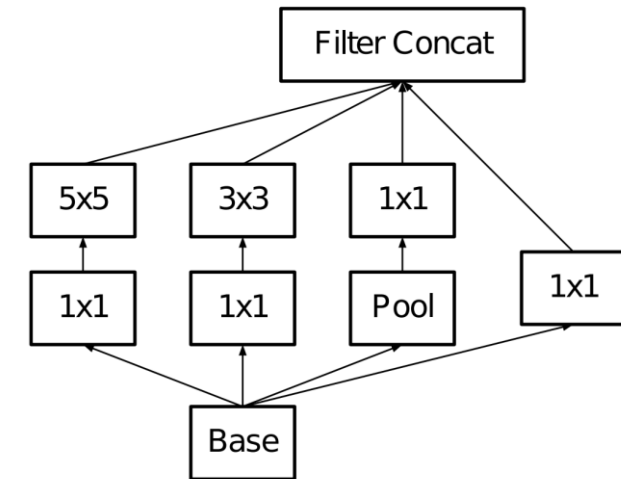
InceptionV3:

- 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 1×10^{-4} for AlexNet and VGG16
 - learning rate 1×10^{-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

	With Histogram Equalization			Without Histogram Equalization		
Architecture	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

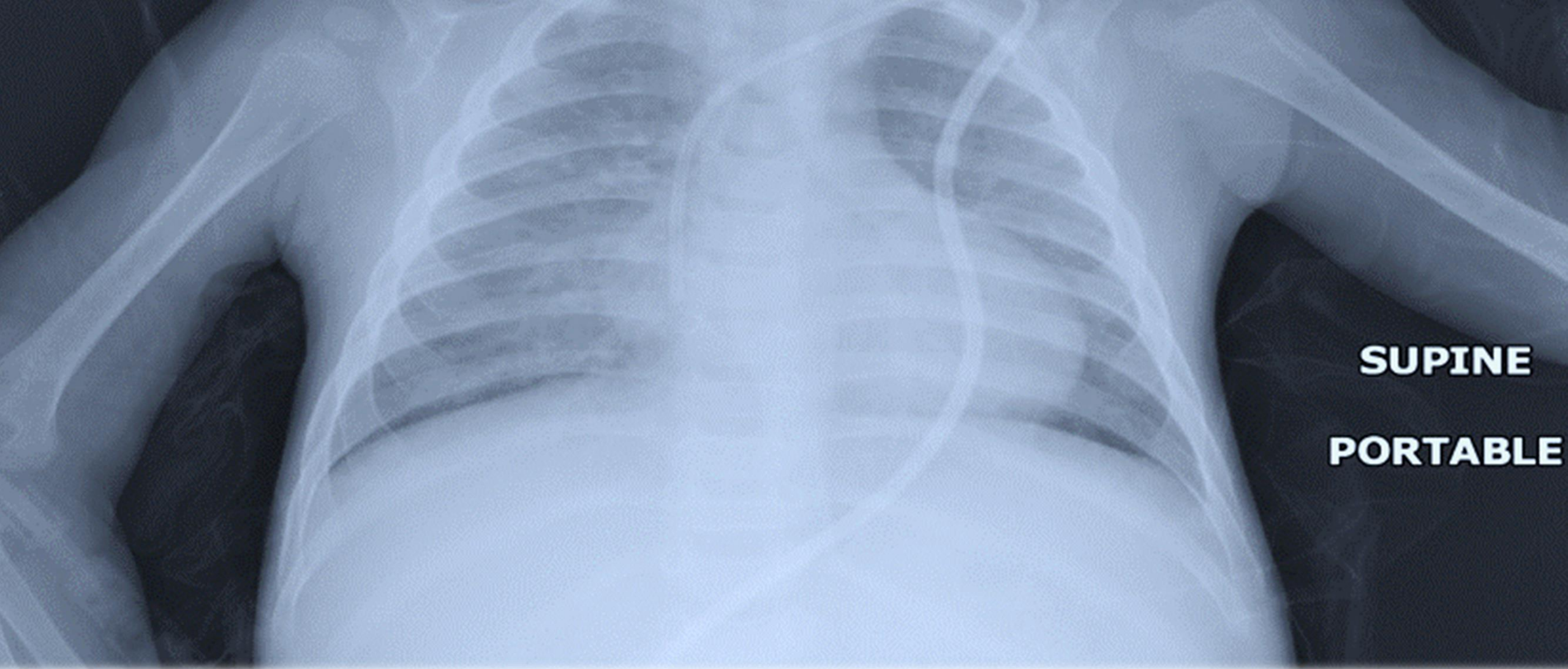
Comparison with state of the art

FUTURE WORK

- Explore more sophisticated preprocessing algorithm to further enhance images
- Explainability and predictions visualization

REFERENCES

- [1] E. Sogancioglu, E. C.alli, B. Ginneken, K. G. V. Leeuwen, and K. Mur-phy, "Deep learning for chest x-ray analysis: A survey,"ArXiv, vol.abs/2103.08700, 2021.
- [2] J. P. Cohen, L. Dao, P. Morrison, K. Roth, Y. Bengio, B. Shen,A. Abbasi, M. Hoshmand-Kochi, M. Ghassemi, H. Li, and T. Q. Duong,"Predicting covid-19 pneumonia severity on chest x-ray with deeplearning," 2020.
- [3] M. Li, N. Arun, M. Gidwani, K. Chang, F. Deng, B. Little, D. Mendoza,M. Lang, O. Vtc Lee, A. O'Shea, A. Parakh, P. Singh, and J. Kalpathy-Cramer, "Automated assessment and tracking of covid-19 pulmonarydisease severity on chest radiographs using convolutional siamese neuralnetworks,"Radiology: Artificial Intelligence, vol. 2, p. e200079, 072020.
- [4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for imagerecognition,"2016 IEEE Conference on Computer Vision and PatternRecognition (CVPR), pp. 770–778, 2016.
- [5] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Denselyconnected convolutional networks," in2017 IEEE Conference on Com-puter Vision and Pattern Recognition (CVPR), 2017, pp. 2261–2269.
- [6] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinkingthe inception architecture for computer vision,"2016 IEEE Conferenceon Computer Vision and Pattern Recognition (CVPR), pp. 2818–2826,2016.
- [7] K. Simonyan and A. Zisserman, "Very deep convolutional networks forlarge-scale image recognition,"CoRR, vol. abs/1409.1556, 2015.
- [8] A. Krizhevsky, I. Sutskever, and G. Hinton, "Imagenet classification withdeep convolutional neural networks,"Neural Information ProcessingSystems, vol. 25, 01 2012.
- [9] I. Sirazitdinov, M. Kholiavchenko, R. Kuleev, and B. Ibragimov, "Dataaugmentation for chest pathologies classification,"2019 IEEE 16thInternational Symposium on Biomedical Imaging (ISBI 2019), pp. 1216–1219, 2019.
- [10] M. S. Vidya, V. Manikanda Krishnan, G. Anirudh, K. Srinivasa Rao, andJ. Vijayananda, "Local and global transformations to improve learningof medical images applied to chest radiographs ," inMedical Imaging2019: Image Processing, E. D. Angelini and B. A. Landman, Eds., vol.10949, International Society for Optics and Photonics. SPIE, 2019, pp.813 – 821.
- [11] O. Gozes and H. Greenspan, "Deep feature learning from a hospital-scale chest x-ray dataset with application to TB detection on asmall-scale dataset," in41st Annual International Conference of theIEEE Engineering in Medicine and Biology Society, EMBC 2019,Berlin, Germany, July 23-27, 2019.IEEE, 2019, pp. 4076–4079.[Online]. Available: <https://doi.org/10.1109/EMBC.2019.8856729>
- [12] I. M. Baltruschat, H. Nickisch, M. Grass, T. Knopp, and A. Saalbach,"Comparison of deep learning approaches for multi-label chest x-rayclassification,"Scientific Reports, vol. 9, 2019.
- [13] H. Liu, L. Wang, Y. Nan, F. Jin, Q. Wang, and J. Pu,"Sdfn: Segmentation-based deep fusion network for thoracic diseaseclassification in chest x-ray images,"Computerized Medical Imagingand Graphics, vol. 75, p. 66–73, Jul 2019. [Online]. Available:<http://dx.doi.org/10.1016/j.compmedimag.2019.05.005>
- [14] M. Pavlova, N. Terhijan, A. G. Chung, A. Zhao, S. Surana,H. Aboutalebi, H. Gunraj, A. Sabri, A. Alaref, and A. Wong, "Covid-net cxr-2: An enhanced deep convolutional neural network design fordetection of covid-19 cases from chest x-ray images," 2021.
- [15] M. Raghu, C. Zhang, J. M. Kleinberg, and S. Bengio, "Transfusion:Understanding transfer learning with applications to medical imaging,"CoRR, vol. abs/1902.07208, 2019. [Online]. Available: <http://arxiv.org/abs/1902.07208>
- [16] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deeppetwork training by reducing internal covariate shift," inProceedingsof the 32nd International Conference on Machine Learning, ser.Proceedings of Machine Learning Research, F. Bach and D. Blei, Eds.,vol. 37. Lille, France: PMLR, 07–09 Jul 2015, pp. 448–456. [Online].Available: <http://proceedings.mlr.press/v37/ioffe15.html>
- [17] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov,D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper withconvolutions,"CoRR, vol. abs/1409.4842, 2014. [Online]. Available:<http://arxiv.org/abs/1409.4842>
- [18] L. Perez and J. Wang, "The effectiveness of data augmentation in imageclassification using deep learning,"ArXiv, vol. abs/1712.04621, 2017.
- [19] D. Kingma and J. Ba, "Adam: A method for stochastic optimization,"International Conference on Learning Representations, 12 2014.



SUPINE
PORTABLE

GRAZIE PER L'ATTENZIONE