

Polițechnika Śląska

### **EVOLVING DEEP ENSEMBLES FOR DETECTING COVID-19** IN CHEST X-RAYS

### Piotr Bosowski<sup>1</sup>, Joanna Bosowska<sup>2</sup>, <u>Jakub Nalepa<sup>1</sup></u>

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#### Improvement of image interpretation

Providing a second diagnostic opinion about an image

Skills: Understanding the properties of machine learning tools to use them in the safest and most effective manner

#### Improvement of workflow

Scheduling, operations, billing

Skills: Capable of adopting cloudbased solutions for image and information management, Understanding of NLP potentials in health administration

#### Production of high-quality images

Applying deep learning-based tools for denoising medical image, generating routine-dose images from low-dose ones, and image reconstruction

Skills: Ability to use offline and *cloud-based image* processing tools for image denoising and reconstruction

Sarah J. Lewis et al.: Artificial Intelligence in medical imaging practice: looking to the future, Journal of Medical Radiation Sciences, First published: 10 November 2019 https://doi.org/10.1002/jmrs.369



#### Automating image registration

Automating the single- and multimodality image fusion and registration

Skills: Understanding of offline and cloud-based image visualization tools



Transforming the medical images into mineable high-dimensional data to improve clinical decision making

Skills: Familiarity with bioinformatics tools

#### Image segmentation

Automating the segmentation of elements such as organs, lesions, etc in the images to eliminate inter-observer variability and improve work efficiency

Skills: Knowledge of machine learning to understand possible sources of errors in the segmentation conducted by a machine



























Wide ResNets



















### OUR METHOD: DEEP ENSEMBLES FOR DETECTING COVID-19 FROM X-RAYS

## EVOLVING DEEP ENSEMBLES FOR DETECTING COVID-19 IN CHEST X-RAYS **Evolving deep ensembles for detecting COVID-19**







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### **EXPERIMENTAL RESULTS**











### X-ray datasets with COVID-19 and non-COVID-19 cases

ID	Dataset	$\mathcal{C}$	COVID-19	non-COVID-19
1	covid-chestxray [25]	3	475	209
2	actualmed-covid-chestxray [26]	2	58	127
3	figure1-covid-chestxray [26]	3	33	5
4	bimcv-covid-19-nega [27]	2		4535
5	padchest [28]	2		2589
6	bimev-covid-19-posi [27]	1	9171	
7	tcia-covid-19 [29]	1	251	
8	covid-19-radiography [30]	1	66	
9	chexpert [31]	2		2589
		Total:	10054	10054

C – number of classes





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C – number of classes 25% T, 5%V, 75% Test with stratification





### The results: quantitative analysis

	Ensemble	Train.	Valid.			Test		
Algorithm	size	Accuracy	Accuracy	Accuracy	Precision	Recall	F1	MC
Wide ResNet-50			0.8280	0.8220	0.8130	0.8370	0.8240	0.6
ResNeXt-101( $32 \times 8d$ )			0.8270	0.8190	0.8120	0.8290	0.8200	0.6
DenseNet-161			0.8270	0.8240	0.8190	0.8310	0.8250	0.64
ANN	170	0.8723	0.8380	0.8335	0.8371	0.8288	0.8327	0.6
SVM	170	0.8830	0.8393	0.8322	0.8472	0.8107	0.8285	0.6
Evolved SVM	59	0.8760	0.8623	0.8345	0.8470	0.8165	0.8315	0.66
XGBoost	170	0.9350	0.8417	0.8355	0.8492	0.8158	0.8322	0.6
Evolved XGBoost	73	0.9370	0.8583	0.8376	0.8425	0.8305	0.8365	0.6'
MV	170	0.8210	0.8260	0.8256	0.8177	0.8381	0.8278	0.6
Evolved MV	31	0.8240	0.8547	0.8294	0.8188	0.8459	0.8321	0.6
WV	170	0.8210	0.8323	0.8282	0.8159	0.8477	0.8315	0.6
Evolved WV	33	0.8270	0.8523	0.8299	0.8148	0.8538	0.8338	0.66
CV	170	0.8180	0.8277	0.8270	0.8181	0.8411	0.8295	0.6
Evolved CV	26	0.8280	0.8527	0.8298	0.8154	0.8527	0.8336	0.66











P. Bosowski, J. Bosowska, <u>J. Nalepa</u>: EVOLVING DEEP ENSEMBLES FOR DETECTING COVID-19 IN CHEST X-RAYS, IEEE ICIP 2021

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### The results: qualitative analysis

(a) True positive (Dataset ID: 7) (b) True positive (Dataset ID: 6)



(c) False negative (Dataset ID: 1)







## The results: qualitative analysis (human rater, 4 YOE)

(a) True positive (Dataset ID: 7)



(c) False negative (Dataset ID: 1)



(b) True positive (Dataset ID: 6)



(d) False positive (Dataset ID: 2)



(a) Multifocal ill-defined and partially diffuse opacifications throughout both lungs with a predilection to the peripheral zones. (...) The presented image may correspond to advanced inflammatory changes, including COVID-19

(b) An ill-defined area of increased density in the upper and mid zone of the right lung with air bronchogram and without volume reduction. (...) COVID-19 not excluded, further diagnostics is necessary (c) The left and right lungs are properly dilated with no visible consolidations. The boundaries of the heart are clear. There are no obvious signs of inflammation in the pulmonary parenchyma (d) Small round consolidation in the lower zone of the right lung—small nodule or summation of the shadows. Past fracture of the III, IV, V, VI, and VII ribs on the right side. No visible signs of pneumonia

**GitLab** https://gitlab.com/jnalepa/icip2021



### CONCLUSIONS

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- Validation protocol is important to really capture generalization abilities



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