COVID-19 X-ray Image Diagnostic with Deep Neural Networks

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Agenda

Introduction

- COVID-19 has impacted on society, public health, and economy
- Artificial intelligence could help the fight against COVID-19
- Chest X-ray images and CT scans can be used for training machine classifiers
- CNNs pre-trained in other problems can achieve good results when applied on COVID-19 diagnostics [1, 2]
- In this work, we evaluated CNN architectures and traditional machine learning classifiers for predicting COVID-19, pneumonia, or healthy patients using chest X-ray images

Dataset

Table: COVIDx [3]: distribution of patients and chest radiography images, considering Normal, Pneumonia, and COVID-19 diagnostics for the training and test sets.

	Patients		Images	
	Train	Test	Train	Test
Normal	7,966	100	7,966	100
Pneumonia	5,444	98	5,459	100
COVID-19	320	74	473	100
Total	13,730	272	13,898	300

Dataset

(a) Normal (b) Pneumonia (c) COVID-19

Figure: Examples of X-rays from the COVIDx dataset [3].

Dataset

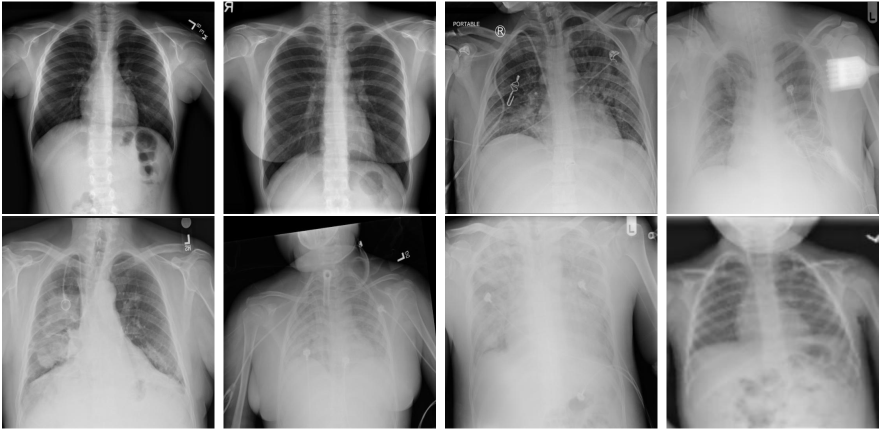

Figure: Examples of images with different patterns, such as medical devices connected to the patient, contour and volume of the breasts and noise.

Methodology

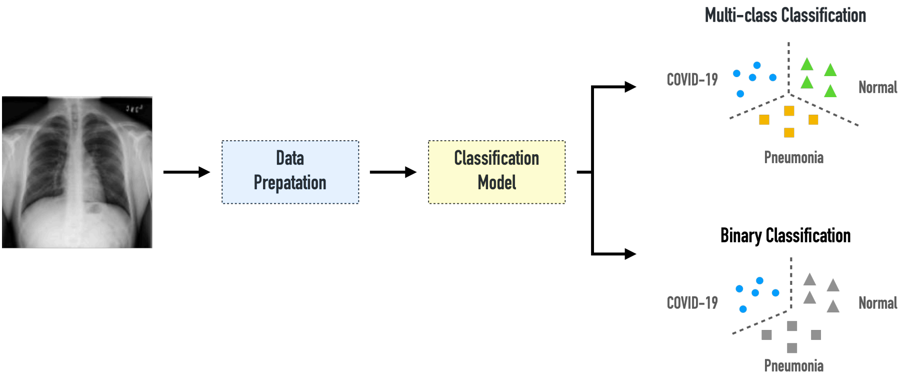

Figure: Overview of our pipeline.

Methodology - Data Preparation

(a) Original (b) Rotation (c) Zoom (d) Vert. Shift (e) Horiz. Shift

Figure: Data augmentation strategies applied during training.

Methodology - Classifiers

CNNs architectures:

- DenseNet121
- EfficientNetB7
- InceptionV3
- MobileNetV2
- NASNetLarge
- ResNet50
- ResNet50V2
- Xception

Traditional ML Classifiers:

- Logistic Regression
- Random Forest
- SVM
- XGBoost

Methodology - Fusion

- Average of Probabilities
- Meta-classifiers using Probabilities
- Meta-classifiers using Deep Features

Experimental Evaluation - Balanced Dataset

- Balanced dataset with 473 x-ray images of each class divided into 383 images for training and 90 images for validation without data augmentation
- Traditional machine learning classifiers with hyperparameters found through a grid search on the balanced set
- Neural Networks with transfer learning and frozen layers

Experimental Evaluation - Balanced Dataset

Table: Accuracy in the balanced validation set and number of parameters for each evaluated models.

Model	**Accuracy in validation (%)**	**Number of parameters**
ResNet50	87.41	25,636,712
EfficientNetB7	84.81	66,658,687
MobileNetV2	81.85	3,538,984
DenseNet121	80.74	8,062,504
MobileNet	80.37	3,538,984
Random Forest	79.25	–
XGBoost	78.52	–
SVM-RBF	78.15	–
Xception	77.78	22,910,480
SVM-Poly	75.93	–
InceptionV3	74.07	23,851,784
NASNetLarge	72.22	88,949,818
ResNet50V2	70.37	25,613,800
Logistic Regression	68.89	–
SVM-Linear	68.15	–

Experimental Evaluation - Full Dataset

- Full dataset with unbalanced classes divided into 80% for training and 20% for validation
- Weights for each class according to their size
- Images with data augmentation
- Convolutional neural networks with unfrozen layers

Experimental Evaluation - Full Dataset

Table: Balanced accuracy in *Multi-class* and *Binary* classification.

Method	Multi-class		Binary	
	Accuracy in validation (%)	Accuracy in test (%)	Accuracy in validation (%)	Accuracy in test (%)
Classifiers				
ResNet50	<u>96.81</u>	<u>90.66</u>	96.13	<u>91.99</u>
EfficientNetB7	83.54	79.33	89.21	81.75
MobileNetV2	90.01	82.66	<u>97.87</u>	90.25
Random Forest	65.30	62.33	50.55	55.00

Experimental Evaluation - Full Dataset

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Random Forest	65.30	62.33	50.55	55.00
Ensemble - Probabilities				
Average	97.22	89.66	98.66	93.25
SVM-Linear	98.37	90.00	98.87	89.75
SVM-Poly	98.70	90.00	<u>99.81</u>	87.25
SVM-RBF	98.47	90.33	98.81	89.50
MLP	<u>99.88</u>	<u>92.00</u>	99.36	<u>93.50</u>
Random Forest	98.68	90.33	99.41	84.75

Experimental Evaluation - Full Dataset

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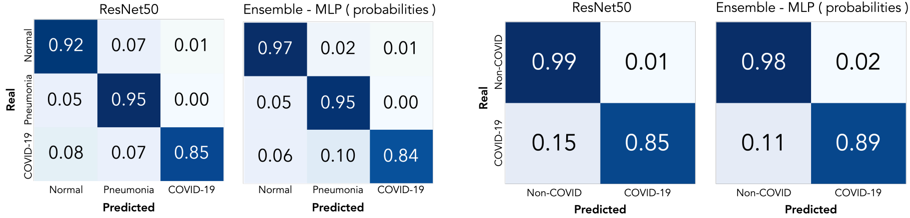
MLP	<u>99.88</u>	<u>92.00</u>	99.36	<u>93.50</u>
Random Forest	98.68	90.33	99.41	84.75
Ensemble - Deep Features				
SVM-Linear	97.67	89.66	<u>99.43</u>	<u>89.75</u>
SVM-Poly	98.26	<u>90.00</u>	99.41	87.75
SVM-RBF	<u>98.34</u>	<u>90.00</u>	99.38	89.50
MLP	98.01	83.33	<u>99.43</u>	86.00
Random Forest	95.35	88.00	96.82	84.74

Experimental Evaluation - Full Dataset



(a) Multi-class Classification.

(b) Binary Classification.

Figure: Confusion matrix for ResNet50 and the best ensemble strategy in both classification scenarios for the test set.

Conclusions

- Transfer learning techniques can achieve good results by leveraging the generalization of the initial layers in a different domain
- Ensemble techniques improved the results compared to the standard convolutional networks

Future Work

- Preprocessing steps:
  - Segmentation of the lung parts of the image
  - Filters to reduce noise
  - Images with high resolution
- Post-processing steps:
  - Explainability techniques
- Data collection

References

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[2] Ioannis D Apostolopoulos and Tzani A Mpesiana.
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Springer J PESM, 43:635–640, 2020.

[3] Linda Wang and Alexander Wong.
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arXiv:2003.09871, 2020.

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