

## Machine Learning

Title: Artificial Intelligence Applied to Chest X-Ray Images for the Automatic Detection of COVID-19.

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### Overview

The COVID-19 pandemic highlighted the need for rapid and reliable diagnostic tools. Traditional RT-PCR testing, though accurate, is time-consuming and often produces false negatives. Chest X-rays (CXR) are widely available and inexpensive, but their interpretation requires trained radiologists.

This project leverages Deep Learning, specifically Convolutional Neural Networks (CNNs), to automatically classify chest X-ray images as COVID-19, pneumonia, or normal. The study evaluates not only accuracy but also explainability, aiming to build a transparent and clinically useful diagnostic model.

### Methodology

A customized version of COVID-Net, implemented in PyTorch, was trained on over 79,000 X-ray images from open datasets such as HM Hospitales, BIMCV-COVID19, Actualmed, CheXpert, and MIMIC-CXR.

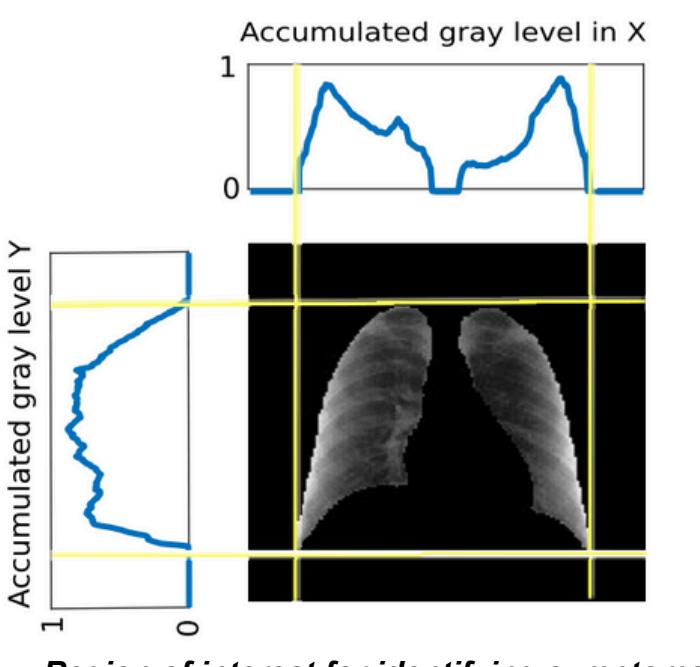
The dataset included 8,573 COVID-19, 24,114 pneumonia, and 49,983 normal images.

The network used Adam optimizer, learning rate  $2 \times 10^{-5}$ , 24 epochs, and batch size = 32. Data augmentation (rotation, noise, flips, elastic deformation) addressed class imbalance, and weighted categorical cross-entropy balanced the training process.

Three experimental setups were evaluated:  
**Raw Data** – direct input images with histogram equalization.

**Cropped ROI** – zoomed and centered lung region to minimize background noise.

**Segmented Lungs** – lung region isolated using U-Net segmentation to force the network's attention toward clinically relevant areas.



### Key Results

- Highest Accuracy: 91.5% in Experiment 3
- Balanced accuracy: 87%
- AUC: 0.97 – indicating strong class separability.
- Recall (COVID-19): 87 %.

While the raw image model achieved slightly higher accuracy (91 %), explainability analysis using Grad-CAM showed it focused on irrelevant regions (image corners, labels). The segmented approach yielded a more medically interpretable model, even with a small performance trade-off. Visualization through t-SNE embeddings confirmed distinct clustering among the three classes, validating the model's learning capability.

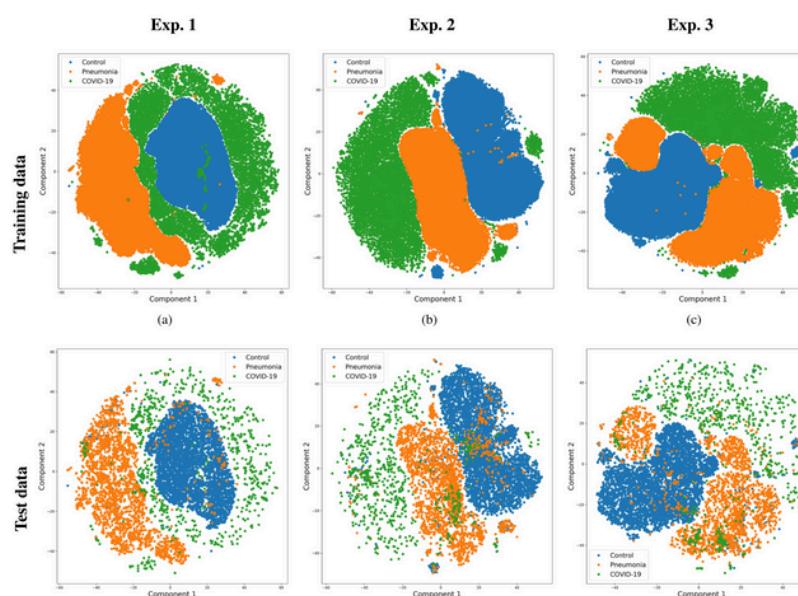
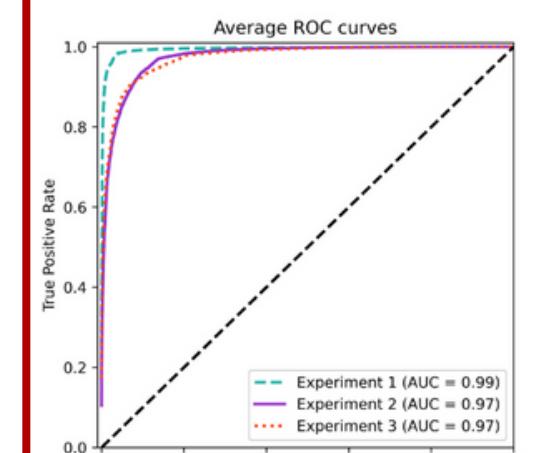


FIGURE 5. Mapping of the high-dimensional data of the layer adjacent to the output into a two dimensional plot. Top: Output network embedding using t-SNE for the training data. Bottom: Output network embedding using t-SNE for the testing data. Left: Original images (experiment 1). Center: Cropped Images (experiment 2). Right: Segmented images (experiment 3).

### Interpretability and variability analysis

- Explainability is vital for clinical AI. Grad-CAM heatmaps revealed that **segmentation-based preprocessing** aligns the model's focus with lung areas exhibiting disease patterns, improving diagnostic trust.
- The model's performance remained stable across variations in **X-ray projection (PA/AP)**, **gender**, and **detector type (CR/DX)**, showing minimal bias. Minor drops in accuracy for specific projections were attributed to fewer COVID-19 samples in those subsets.
- Thus, the system demonstrates both **accuracy** and **robustness**, essential for real-world medical application.



Average ROC curves for each experiment, including AUC values.

### Conclusion

- This research proves that deep learning can effectively detect COVID-19 and pneumonia from X-rays with **radiologist-level accuracy** while offering interpretability through **visual explanation maps**.
- Although performance marginally decreases with segmentation, **explainable AI** methods like Grad-CAM ensure the model's reliability for clinical deployment.
- Future work includes expanding dataset diversity, integrating CT scans for multimodal learning, and deploying the model in **cloud-based screening systems** for hospitals to accelerate diagnosis and reduce workload.

### References

- Research Paper:  
<https://ieeexplore.ieee.org/document/9293268>  
 World Health Organisation (WHO)  
<https://www.who.int/emergencies/diseases/novel-coronavirus-2019>  
 PyTorch Official Documentation:  
<https://pytorch.org/>

TABLE 3. Demographic data of the datasets used. Only those labels confirmed are reported.

	Mean age $\pm$ std	# Males/# Females	# Images	AP/PA	DX/CR	COVID-19	Pneumonia	Control
HM Hospitales	$67.8 \pm 15.7$	3703/1857 *	5560	5018/542	1264/4296	Y	N	N
BIMCV	$62.4 \pm 16.7$	1527/1486 **	3013	1171/1217	1145/1868	Y	N	N
ACT	–	–	188	30/155	126/59	Y	N	Y
ChinaSet	$35.4 \pm 14.8$	449/213	662	0/662	662/0	N	Y	Y
Montgomery	$51.9 \pm 2.41$	63/74	138	0/138	0/138	N	Y	Y
CRX8	$45.75 \pm 16.83$	34760/27030	61790	21860/39930	61790/0	N	Y	Y
CheXpert	$62.38 \pm 18.62$	2697/1926	4623	3432/1191	–	N	Y	N
MIMIC	–	–	16399	10850/5549	–	N	Y	N

\* 1377/929 patients    \*\* 727/626 patients