Unsupervised Patient Re-identification in Chest X-Ray Images

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Introduction

Chest X-rays (CXR) allow extraction of diagnostic features that artificial intelligence models can leverage for automatic disease detection. To prevent data leakage, it's important to know which patient a radiograph belongs to, ensuring that images from the same patient do not appear in both training and validation sets. However, due to privacy concerns and registration errors, CXRs often have missing or incorrect patient IDs. This study presents an **unsupervised neural network for identifying if two CXR images belong to the same patient**, benchmarking its performance against a supervised method.

Methodology

- Patient Reidentification Framework

❖ The ChestX-ray14 [1] dataset was split 90% for training and 10% for testing.
❖ A modified ResNet-18 [2] was used for patient reidentification, utilizing a contrastive learning approach for both supervised and unsupervised methods.

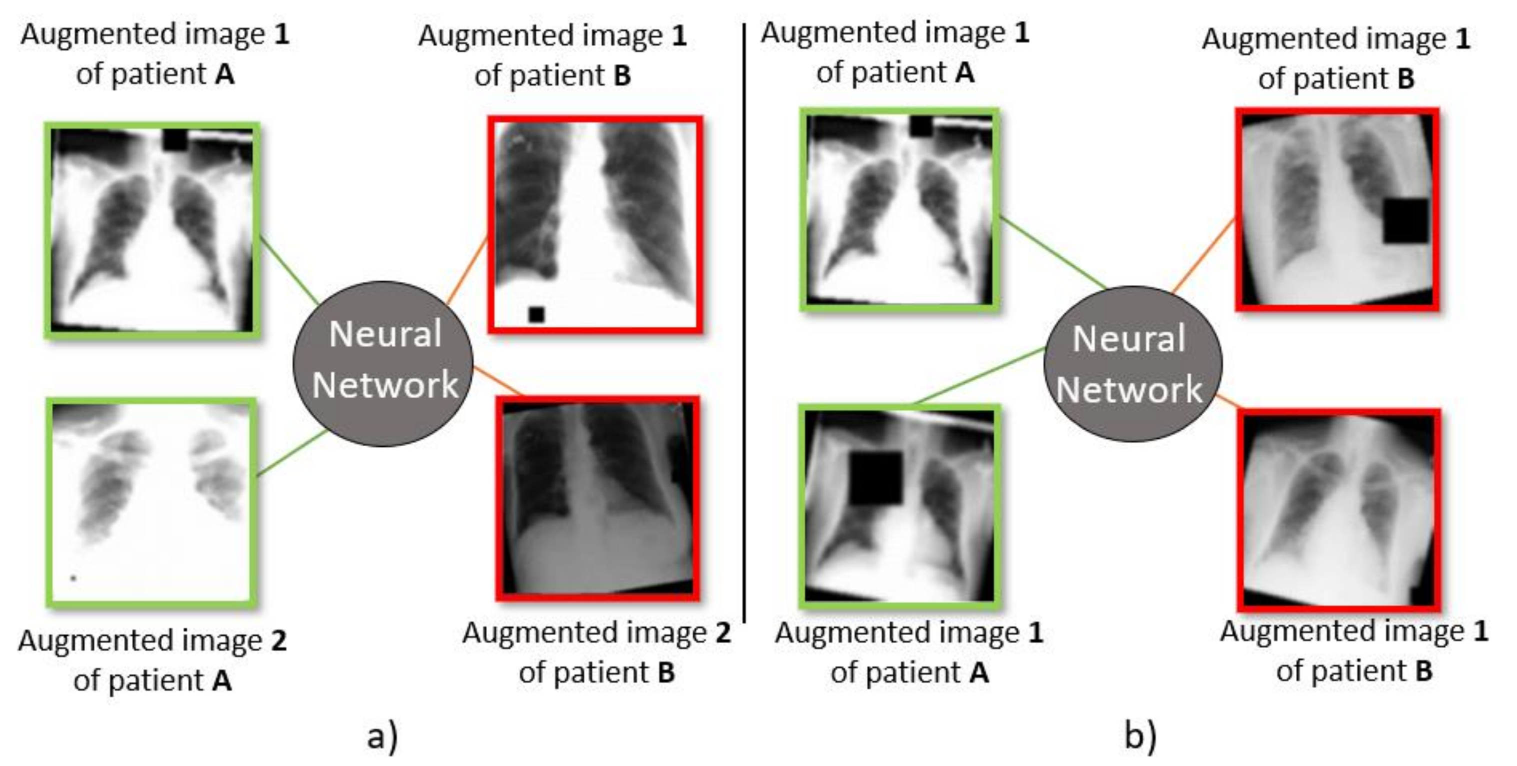

Figure 1: a) Supervised Contrastive Learning b) Unsupervised Contrastive Learning

- Augmentations

Training 0	Training 1
No augmentations (only for supervised training)	Random Cropping
Training 2	**Training 3**
Random Cropping Random Brightness Changes Rotation - 0 to 15°	Random Cropping Random Brightness Changes Random Rotation - 0 to 15°
Training 4	**Training 5**
Random Cropping Random Brightness Changes Random Rotation - 0 to 15° Random Occlusions - 0 to 1/3 Gaussian Blur	Random Cropping Random Brightness Changes Random Rotation - 0 to 15° Gaussian Blur

Table 1: Applied augmentations

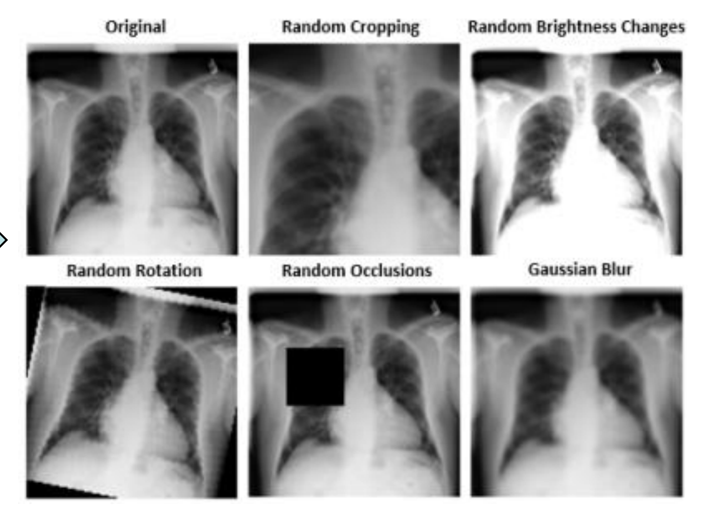

Figure 2: Examples of the augmentations applied

- Evaluation

❖ Cosine similarity was used to compare feature representations.
❖ The ROC curve, Precision-Recall curve, and Top-X precision/recall were computed to evaluate the model's ability to identify if two images belong to the same patient (Fig.3).

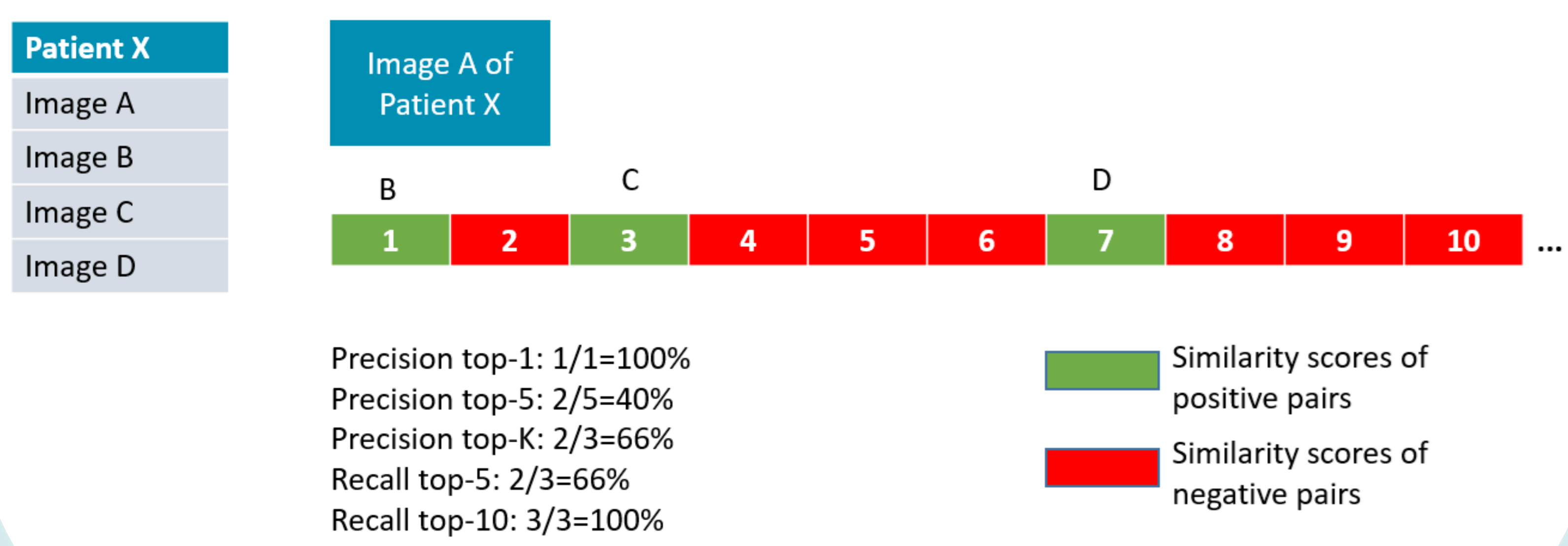

Figure 3: Example of Metric Calculation for Patient X

Results

-Unsupervised Learning

- The high AUC ROC are explained by the imbalanced nature of the problem. The model correctly matched the most similar image to the same patient **66.7%** (Fig.4).

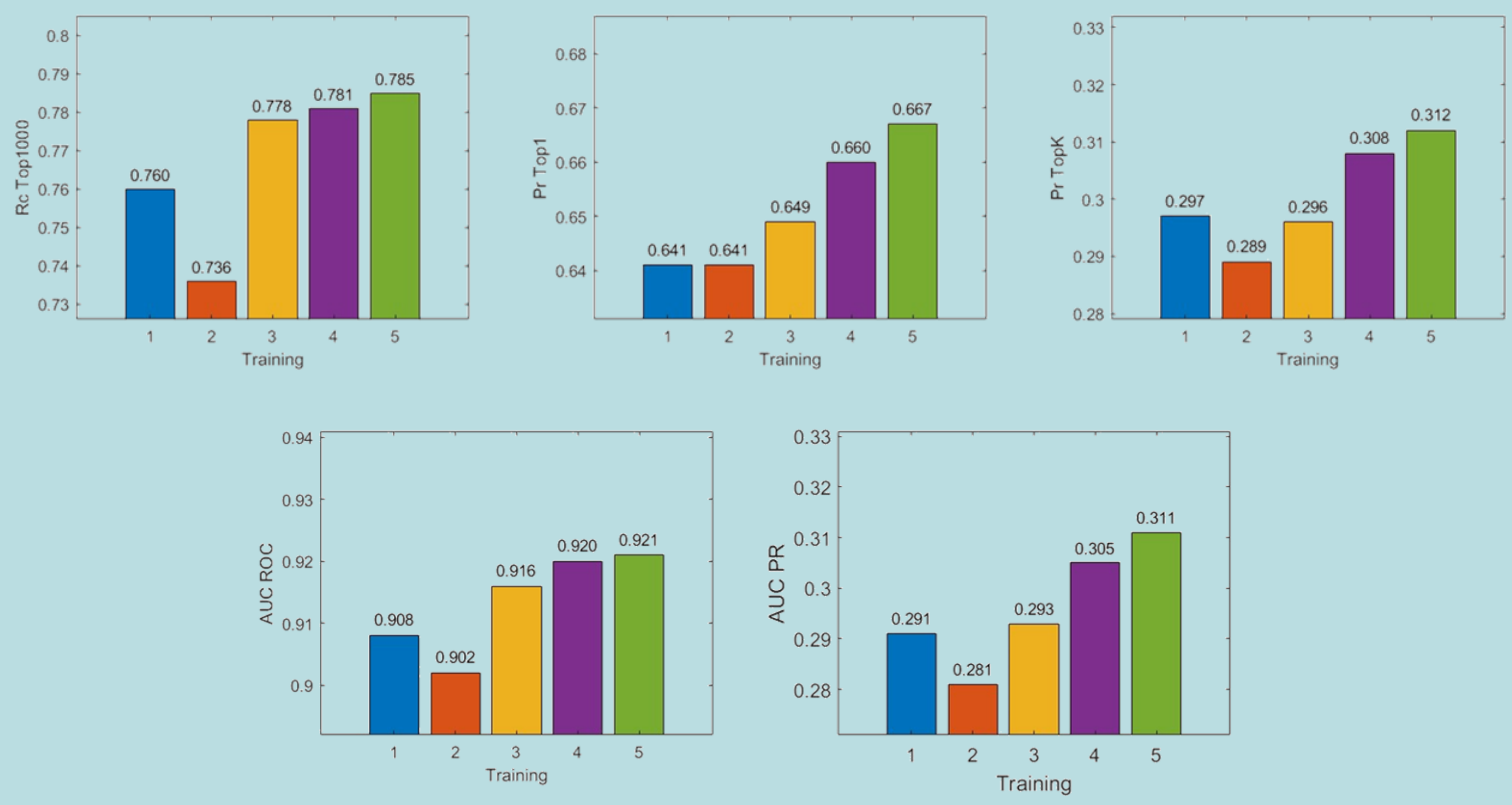

Figure 4: Evaluation of unsupervised learning

-Supervised Learning

- The model correctly matched the most similar image to the same patient **93.5%** of the time (Fig.5).

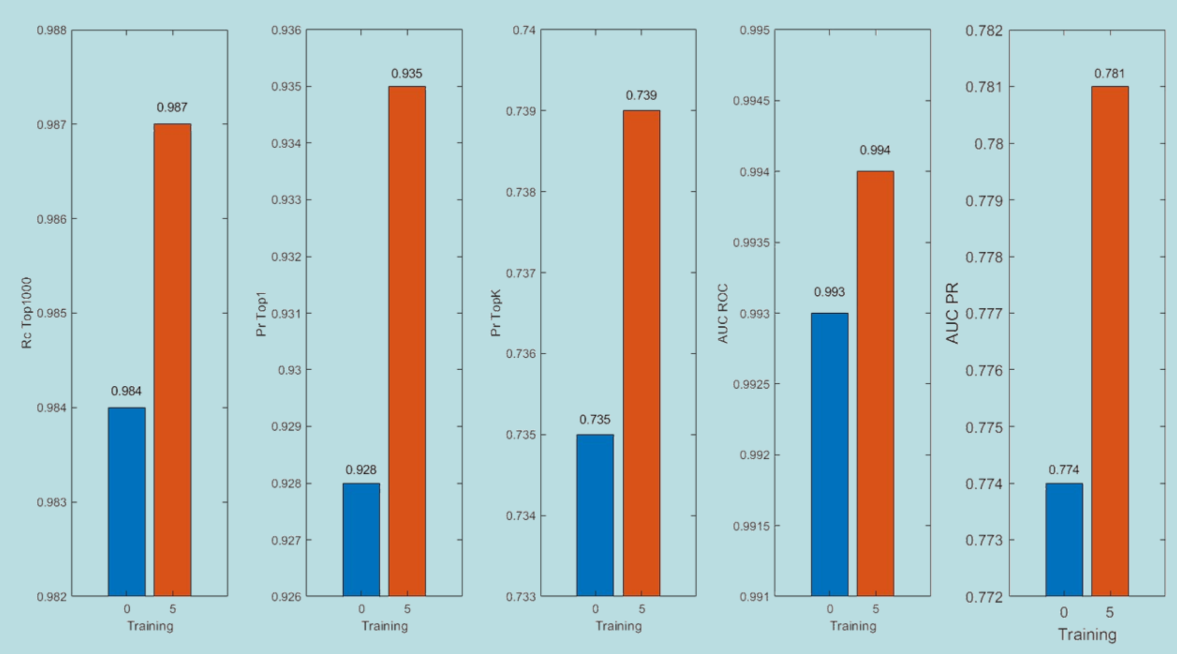

Figure 5: Evaluation of supervised learning

Conclusion

- The supervised approach showed better performance in this study, with higher precision, recall, and AUC.
- The unsupervised method works without labeled data and is useful when labeling is difficult, but it performs slightly worse than the supervised method.
- Enhancing image transformations, extending training epochs, and testing on diverse datasets may improve unsupervised learning and reveal cases where it can surpass supervised methods.

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References

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