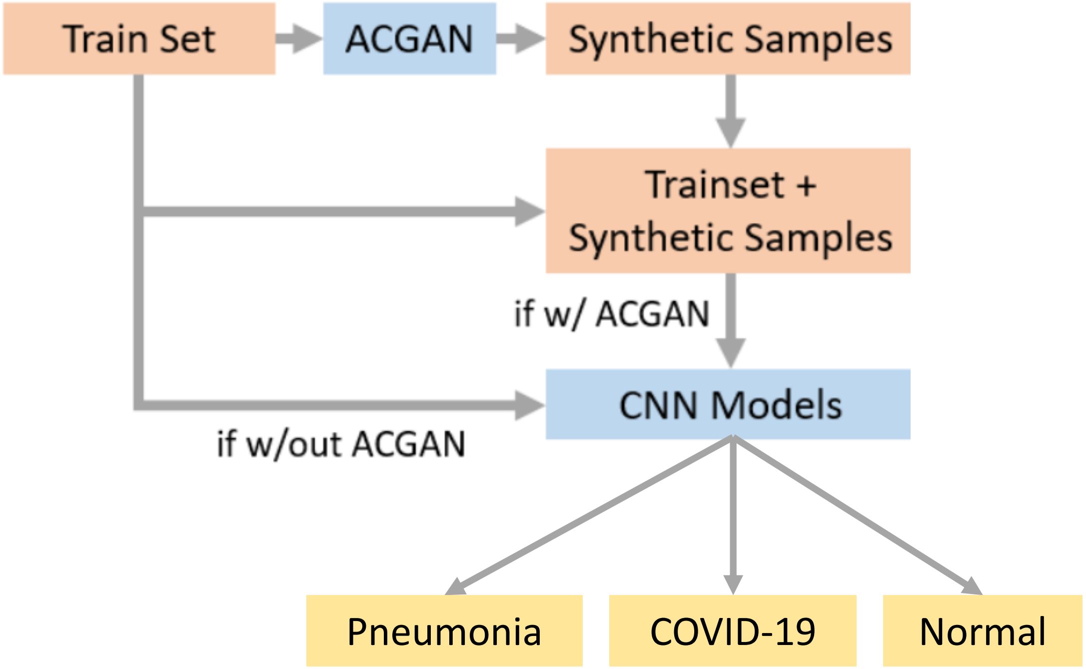
CXR-ACGAN

Auxiliary Classifier GAN for Conditional Generation of Chest X-Ray Images (Pneumonia, COVID-19 and Healthy patients).

Conditional Generation of Synthetic Chest X-Ray Images

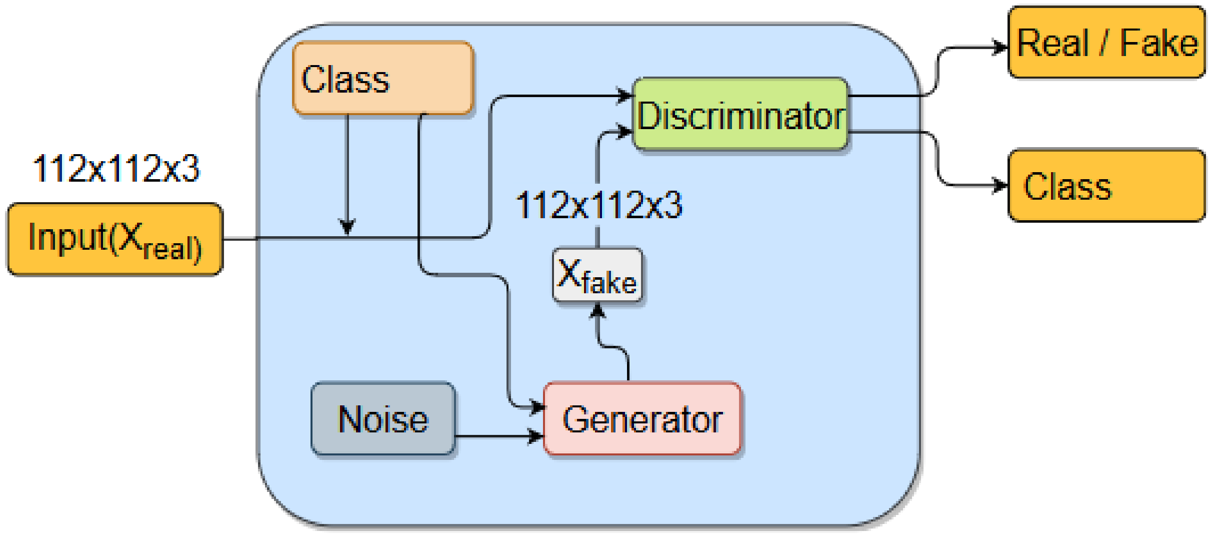
- Objectives:
  - Train an **AC-GAN** to synthesize **chest x-rays images**
  - **Conditional** generation of **healthy**, **covid-19** and **pneumonia** patients x-rays
  - **Data augmentation** on the class-imbalanced **COVIDx** dataset to improve classification performances

- Dataset → **COVIDx**
  - **Simple image pre-processing** → $112x112$ resizing and $[0,1]$ pixel scaling
  - **Data augmentation** → shearing and zooming



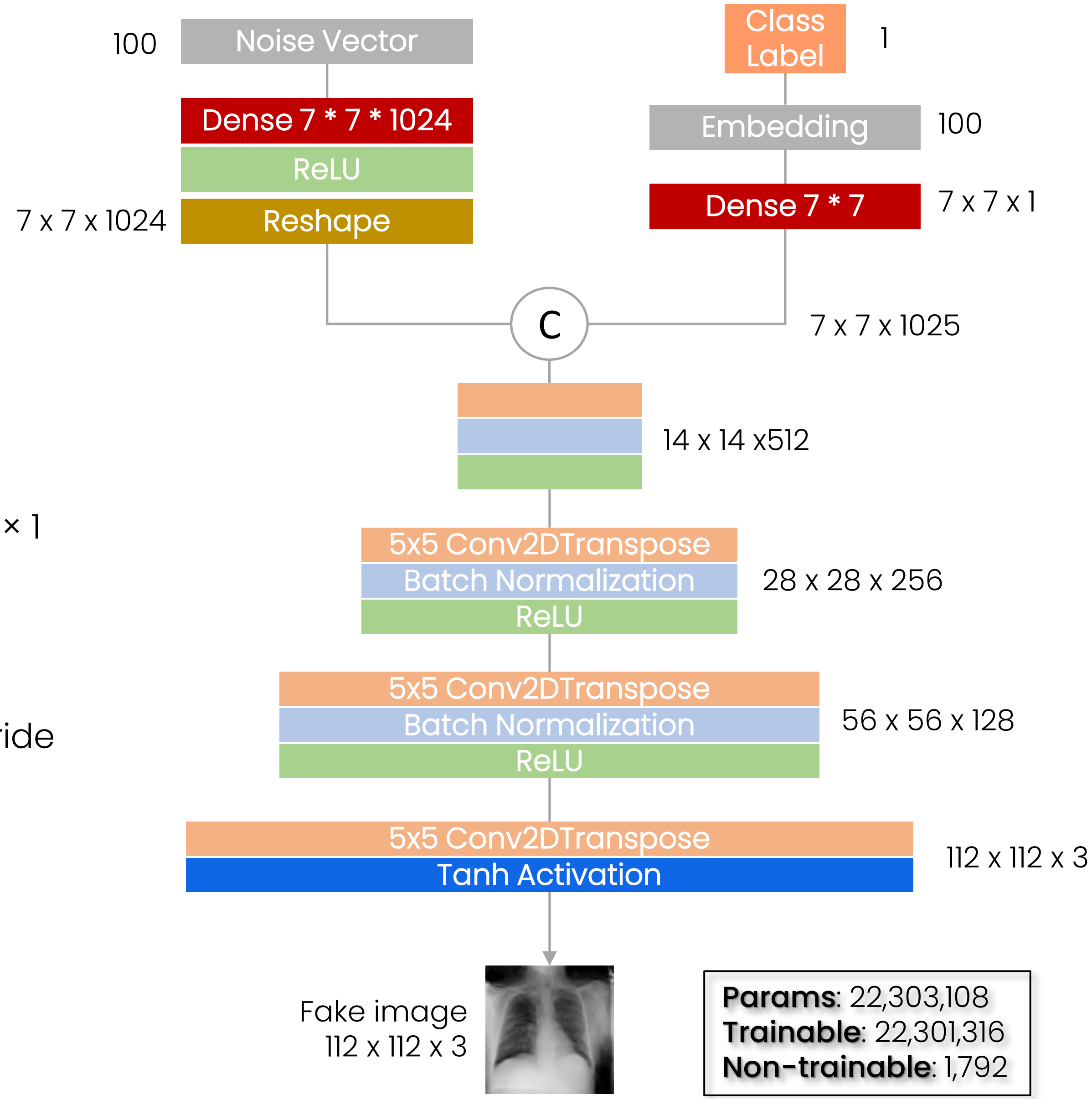
Auxiliary Classifier Generative Adversarial Network (AC-GAN)

- ❑ **AC-GAN** → extension of the GAN architecture
- ❑ The **generator** is **class conditional** as with **cGANs**
  - ❑ Input → randomly sampled **100-dimensional noise vector** and a **label**,
  - ❑ Output → conditionally generating a **112x112x3 image**
  - ❑ The **classes** → coded by integers (**0,1,2**).
- ❑ The **discriminator** → comes with an **auxiliary classifier**
  - ❑ trained to reconstruct the input image **class label**.
  - ❑ Input → 112x112x3 image (real or synthesised)
  - ❑ Output → **predicts its source** (real/fake) and **class** (0,1,2)



Generator

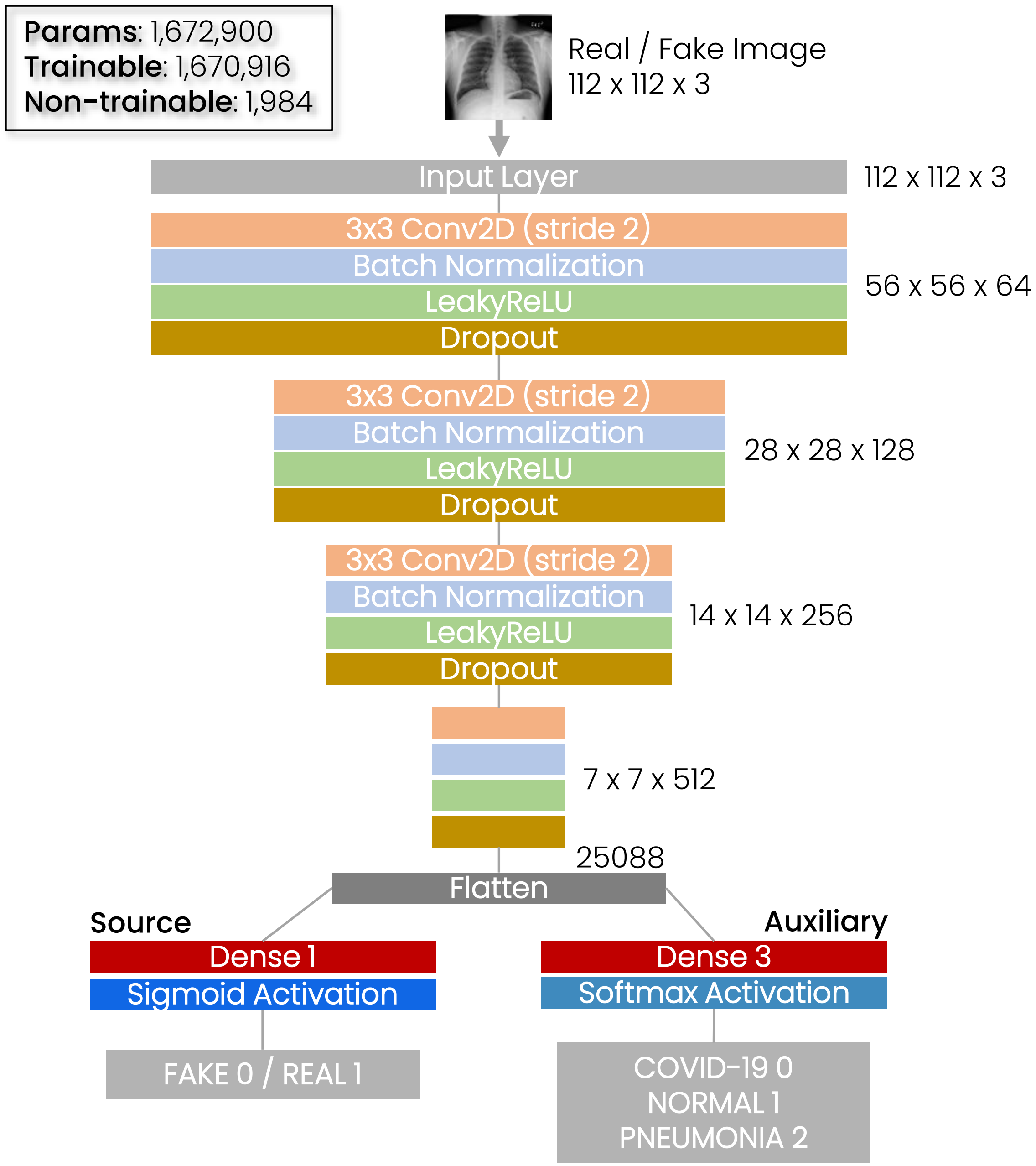
1. Two **inputs**:
    1. random 100-dimensional **noise vector**
    2. integer **class label** c (0, 1, 2)
2. **Class label** → **embedding layer** → **dense layer** → 7 × 7 × 1
3. **Noise vector** → **dense layer** → 7 × 7 × 1024
4. These two tensors are then **concatenated** → 7 × 7 × 1025
5. **Four** transposed **convolutional layers** (kernel size = 5, stride = 2) → 112 × 112 × 3
    - The first three are paired with **batch normalization** and a **Rectified Linear Unit (ReLU)** activation
    - Last one with **tanh activation**
6. Output: **fake image** with size 112 × 112 × 3



Params: 22,303,108
Trainable: 22,301,316
Non-trainable: 1,792

Discriminator

1. Input: **112 × 112 × 3 image** → dataset (real) or synthetic (fake)
2. **Four blocks:**
   - ❑ Sequence of: **convolutional** layer, **batch normalization** layer, **LeakyReLU** activation (slope = 0.2) and **dropout** layer (p = 0.5).
   - ❑ Image size: 112 × 112 × 3 → 7 × 7 × 512
3. The tensor is **flattened** → fed into two dense layers
4. First **dense layer + sigmoid** activation
   - ❑ **Binary classifier** → outputs a probability indicating whether the image is from the original dataset (as "real") or generated by the generator (as "fake").
5. Second **dense layer** + softmax activation
   - ❑ **Multiclass classifier** → outputs a 1D tensor of probabilities of each class



Training and regularization

- **Adam optimizer** → both the generator and the discriminator
- **Two loss functions**, one for each output layer of the **discriminator**
  - First output layer → binary cross-entropy loss (**source loss L_s**)
  - Second output layer → sparse categorical cross entropy (**auxiliary classifier loss L_c**)
- **Minimize the overall loss $L = L_s + L_c$** → during the generator training as well as the discriminator training
  - **Label flipping** (generator training) → all the fake (0) images generated are passed to discriminator labelled as real (1)
- **Labels smoothing** (discriminator training) → applied to the binary vectors describing the origin of the image (0/real – 1/fake) as a **regularization method**

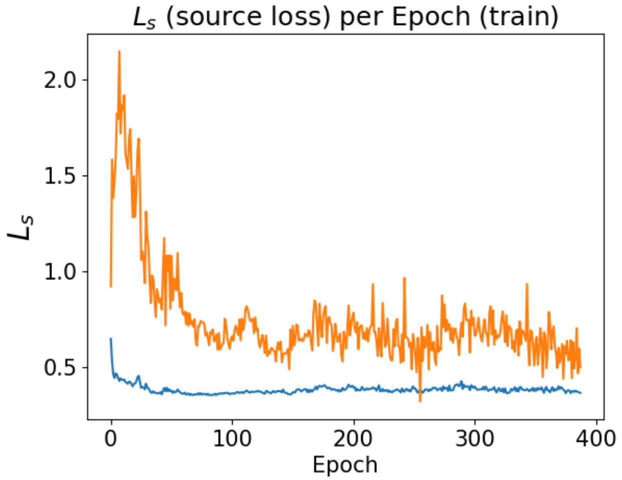
Parameters	Value
Max Epoch	388
Optimizer	Adam
Learning rate	0.0002 (fixed)
Adam β_1	0.5 (fixed)
Batch Size	64
Steps per epoch	460

Training

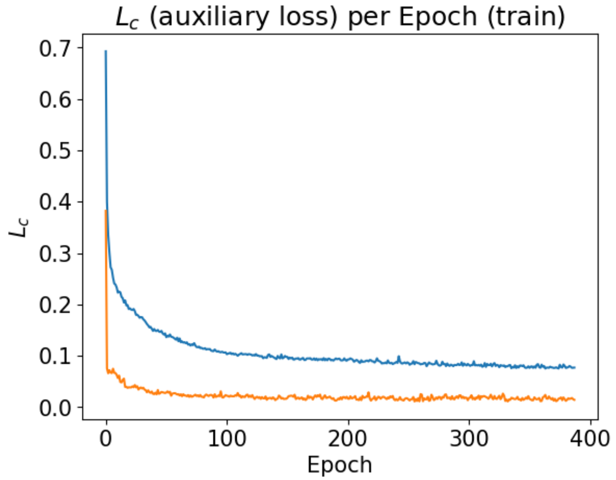
Discriminator

Generator

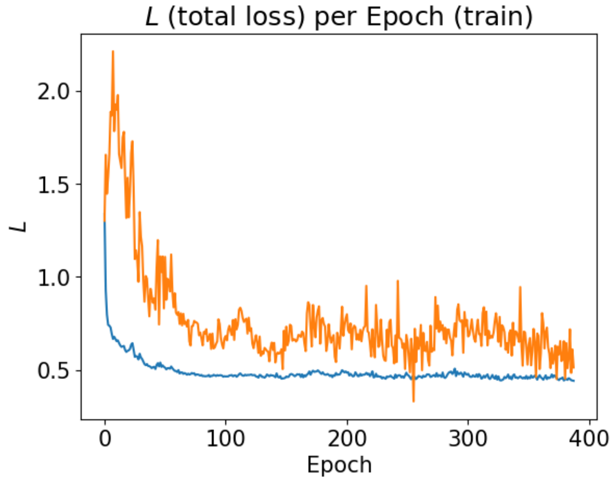
Source Loss L_s



Auxiliary Loss L_c



Total Loss L

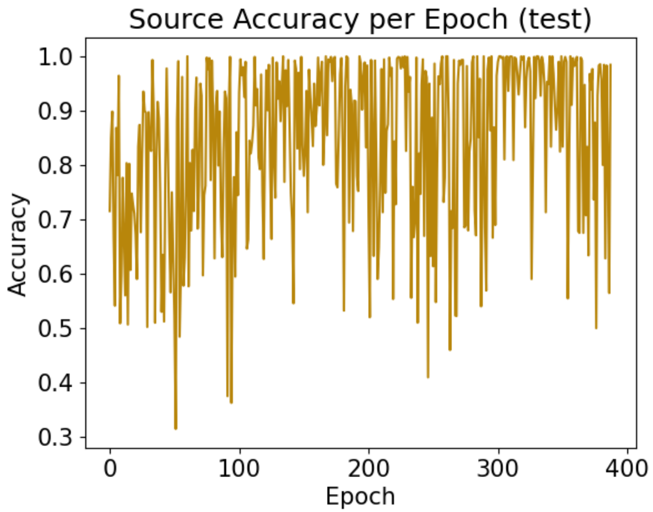


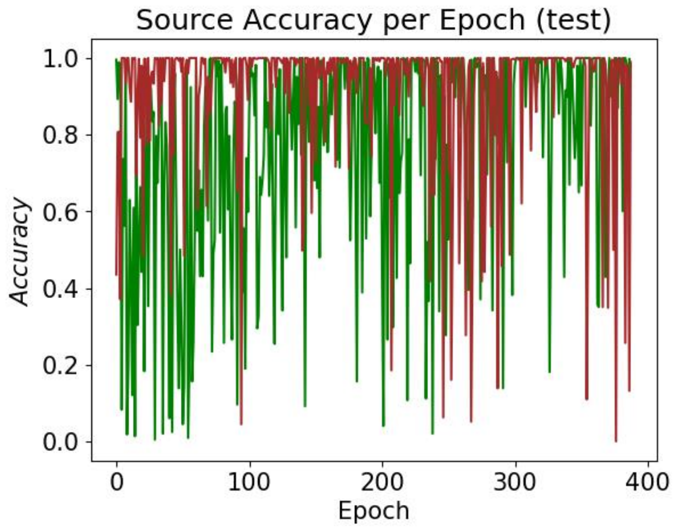
Testing Discriminator

Overall Accuracy

Real Accuracy

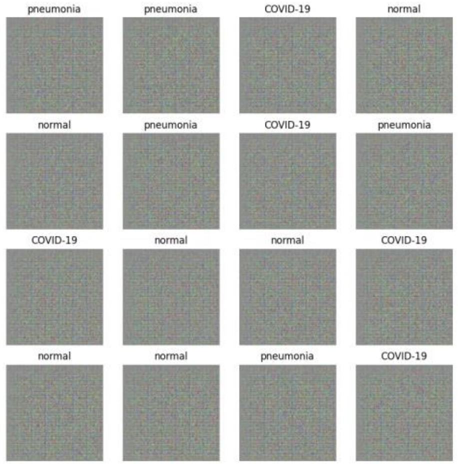
Fake Accuracy





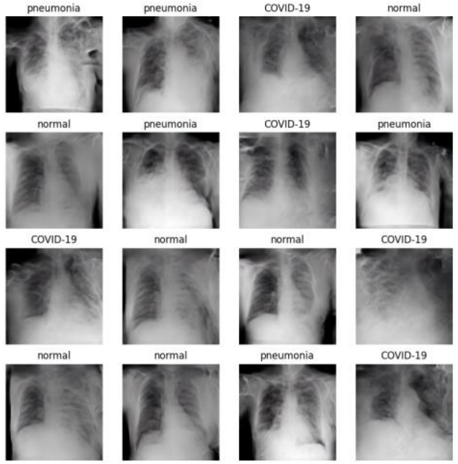
Choosing the best AC-GAN model weights

Epoch 0



1. First set of models selection based on:
    - ↑ **visual quality qualitative evaluation** of sample images generated during each epoch
    - ↓ **generator losses**
    - ↓ **discriminator accuracy** in correctly classifying fake images as fake.
2. Trained a **classifier** on synthetic images only → evaluated the classification accuracy on real COVIDx images
    - **epoch 288** → best model
3. Generated Images Quality Evaluation
    - ↓ **FID**, ↓ **Intra-FID** and ↑ **Inception Score** (**IS**) → InceptionV3
4. **2D t-SNE embedding visualization** of generated and real images

Epoch 288

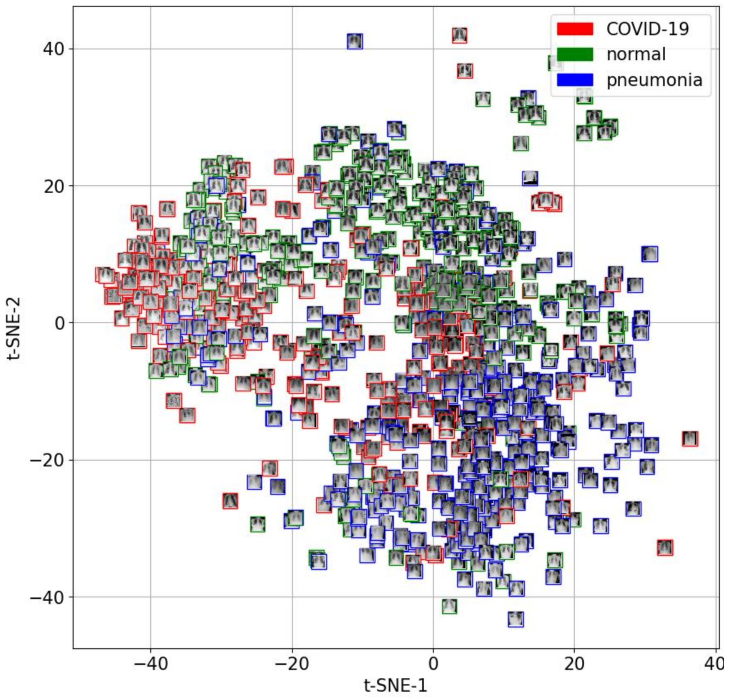


Evaluation

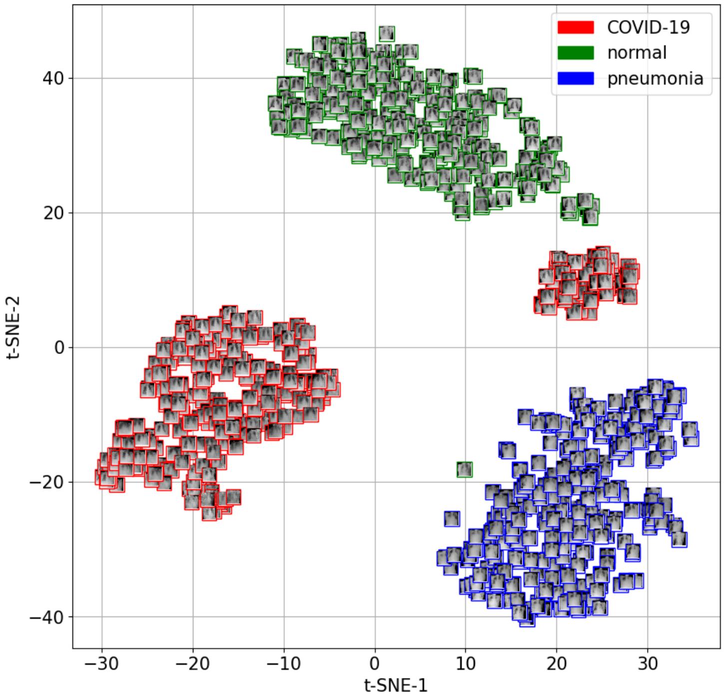
Metric	Value
Generator loss L	0.44
Discriminator accuracy (fake images)	0.13
Qualitative appearance	Realistic
CNN Accuracy (on real images)	0.63

	Our AC-GAN	Paper AC-GAN [6]
IS ↑	2.71 (± 1.70)	2.51 (± 0.12)
FID ↓	123.26 (± 0.02)	50.67 (± 8.13)
Intra FID ↓	136 (± 0.02)	

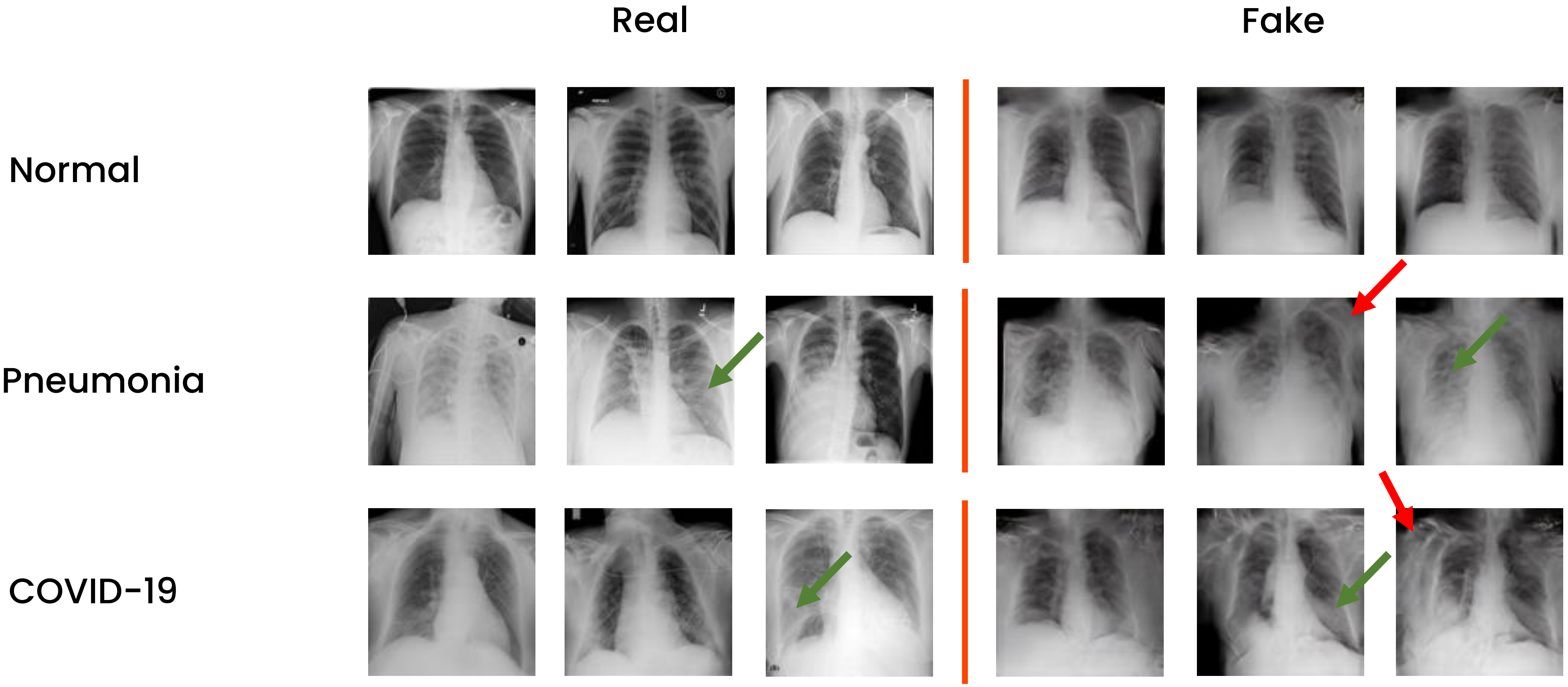
Real t-SNE



Synthetic t-SNE



Real and Synthetic chest x-ray sample



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