Chest X-Ray Classification with synthetic Data

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Introduction

This project leverages advanced generative modeling techniques, specifically Variational Autoencoders (**VAEs**), **Enhanced VAEs**, and Denoising Diffusion Probabilistic Models (**DDPMs**), to generate high-quality synthetic chest X-ray images. These generative models will be compared in their effectiveness for addressing the common yet challenging issue of class imbalance in medical imaging datasets..

Dataset

Chest X-ray Images (Pneumonia)

Source: [Kaggle Chest X-ray Pneumonia Dataset]

Description

The dataset contains chest X-ray images used for diagnosing pneumonia. It is structured into three subsets:

- Train: Primary training set.
- Test: Evaluation set for model validation.
- Val: Additional set for tuning hyperparameters and model validation.

Images are categorized into two distinct classes:

- Normal: Chest X-rays with no signs of pneumonia.
- Pneumonia: Chest X-rays exhibiting characteristics consistent with pneumonia.

The problem and our solution

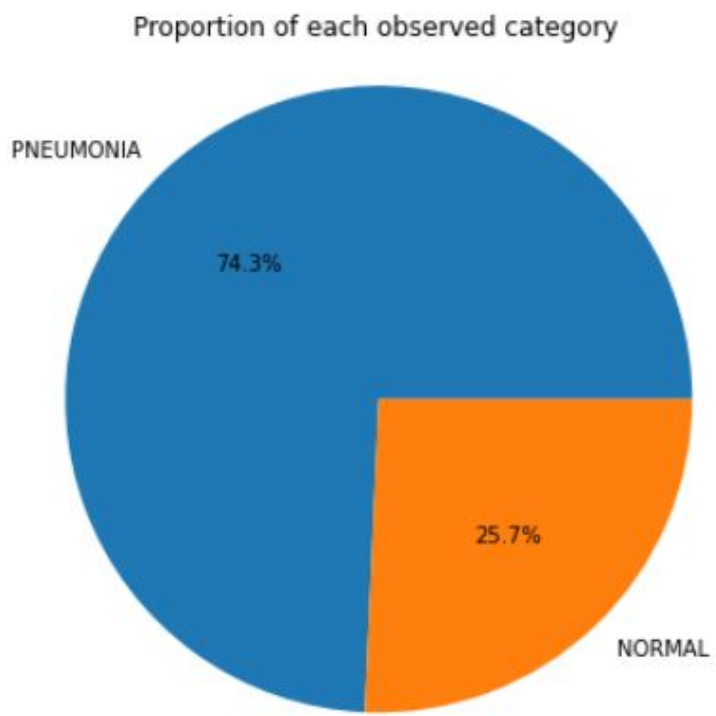
Problem:

- PNEUMONIA: 3875 images
- NORMAL: 1341 images

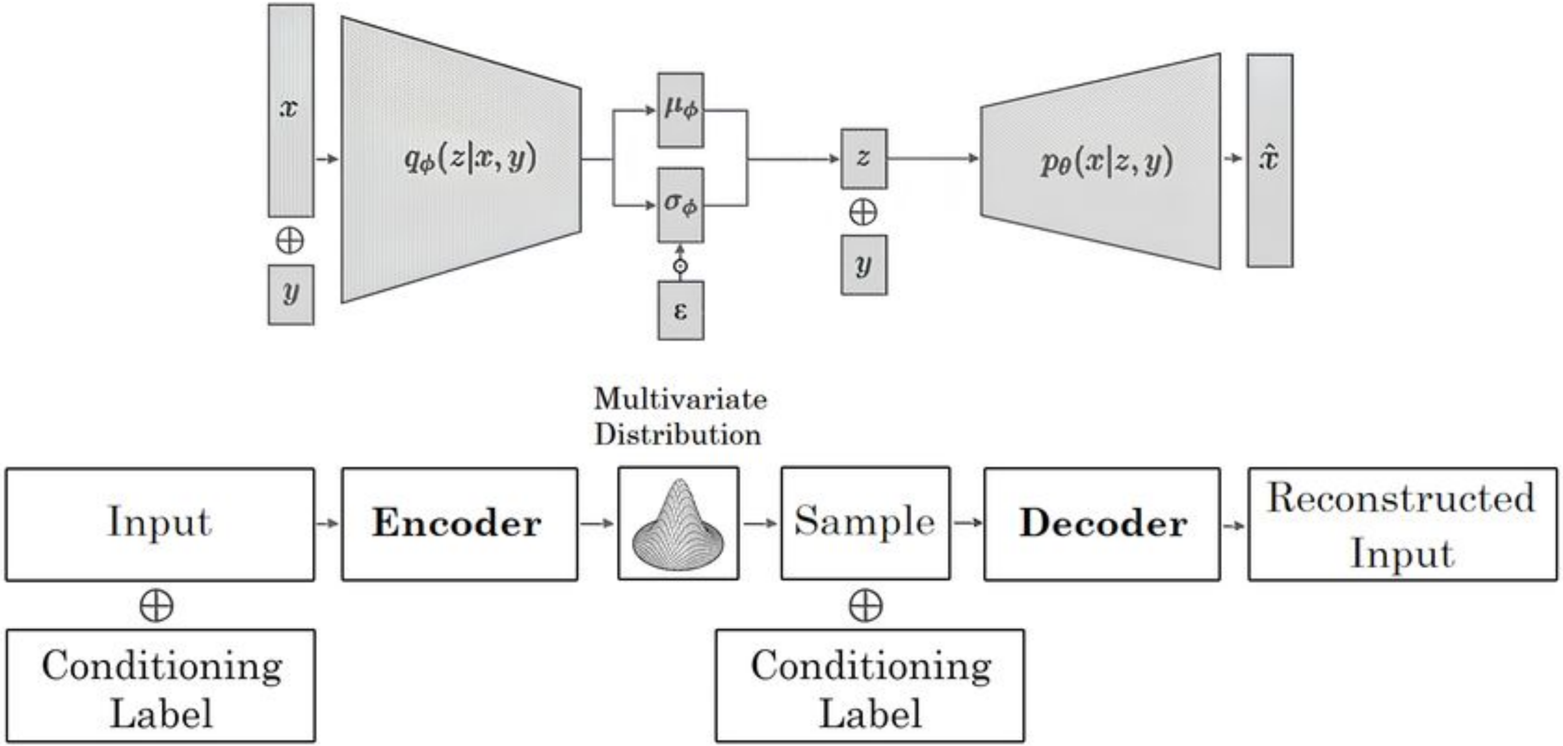
Class imbalance in medical imaging datasets impacts diagnostic accuracy.

Solutions:

- Employ and compare three generative models (**VAE**, **Enhanced VAE**, and **DDPM**) to generate balanced synthetic chest X-rays.



Conditional VAE



Why Conditional VAE

Controlled Generation

By conditioning on your label y (e.g., “Normal”), your C-VAE can generate chest X-rays specific to that class, helping to balance your dataset.

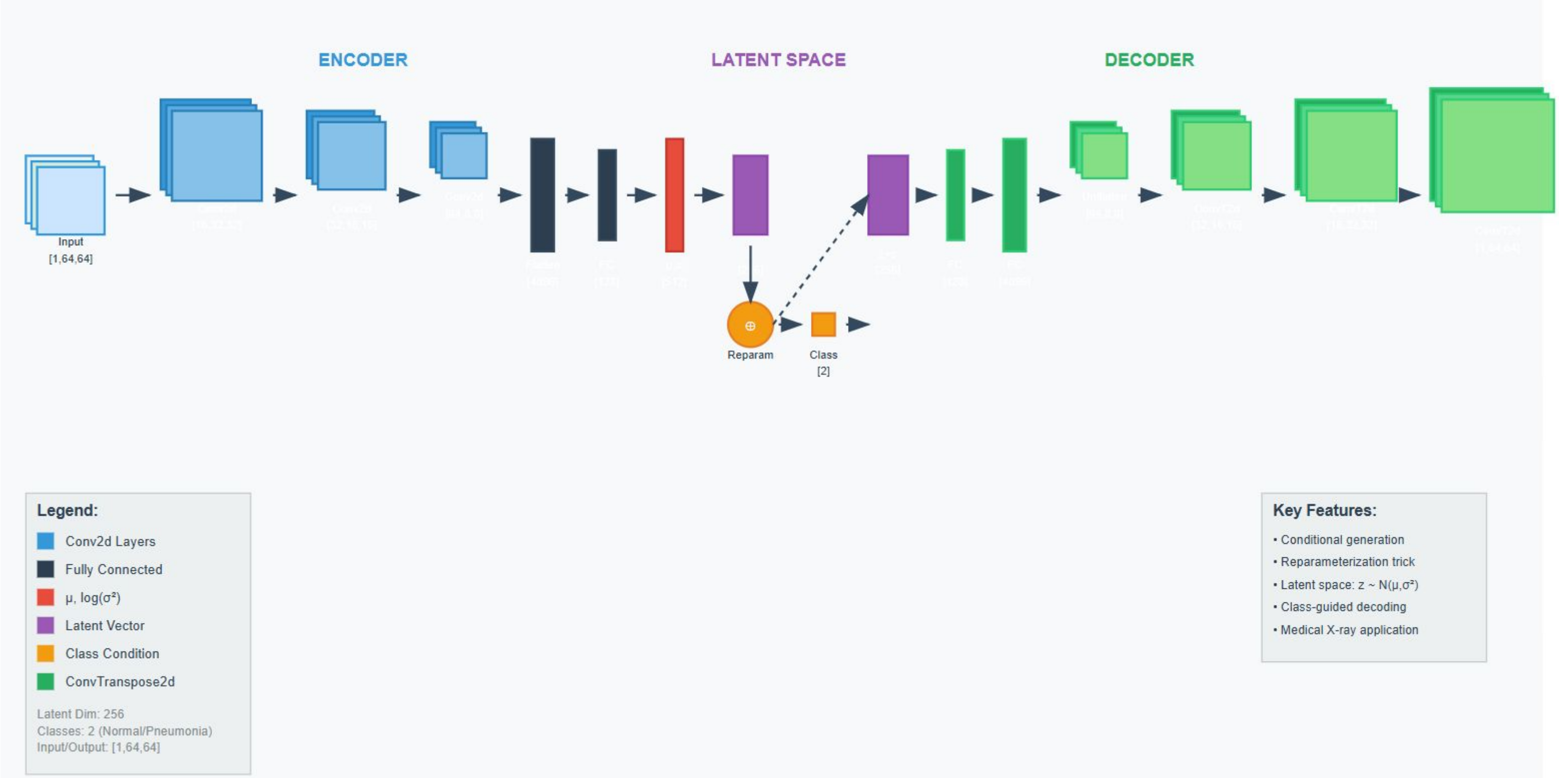
When conditioning on an additional variable y (e.g., class label), both the encoder and decoder include y:

$$\ln p(x|y) \geq \underbrace{\mathbb{E}_{q_\phi(z|x,y)}[\ln p_\theta(x|z,y)]}_{\text{Reconstruction Term}} - \underbrace{D_{\mathrm{KL}}(q_\phi(z|x,y) \,\|\, p_\theta(z|y))}_{\text{Conditional Regularization}}$$

Thus the CVAE loss is:

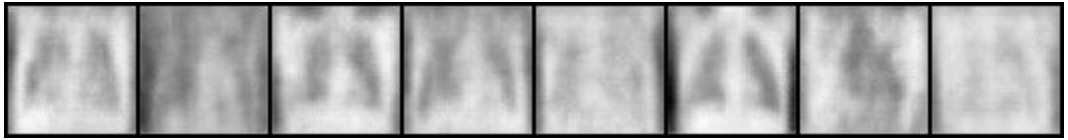
$$\mathcal{L}_{\mathrm{CVAE}}(x,y) = -\mathbb{E}_{q_\phi(z|x,y)}[\ln p_\theta(x|z,y)] + D_{\mathrm{KL}}(q_\phi(z|x,y) \,\|\, p_\theta(z|y))$$

Conditional VAE Architecture

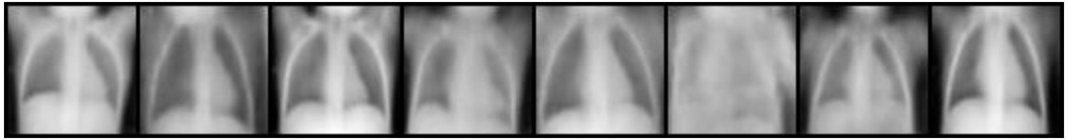


Conditional VAE Results

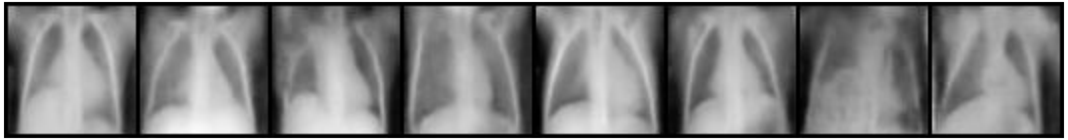
- VAE epoch 1



- VAE epoch 30



- VAE epoch 78



Enhanced Conditional VAE

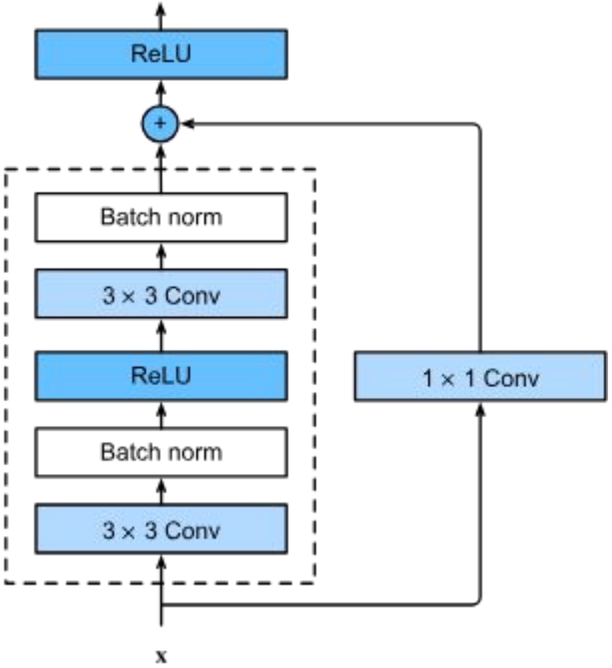
This section defines and trains a more expressive Conditional Variational Autoencoder (**VAE**) that leverages:

- **Residual blocks** in the decoder for sharper image reconstruction.
- **SSIM (Structural Similarity Index)** as a secondary loss term to preserve image structure.
- **β-VAE regularization**.
- **Early stopping**

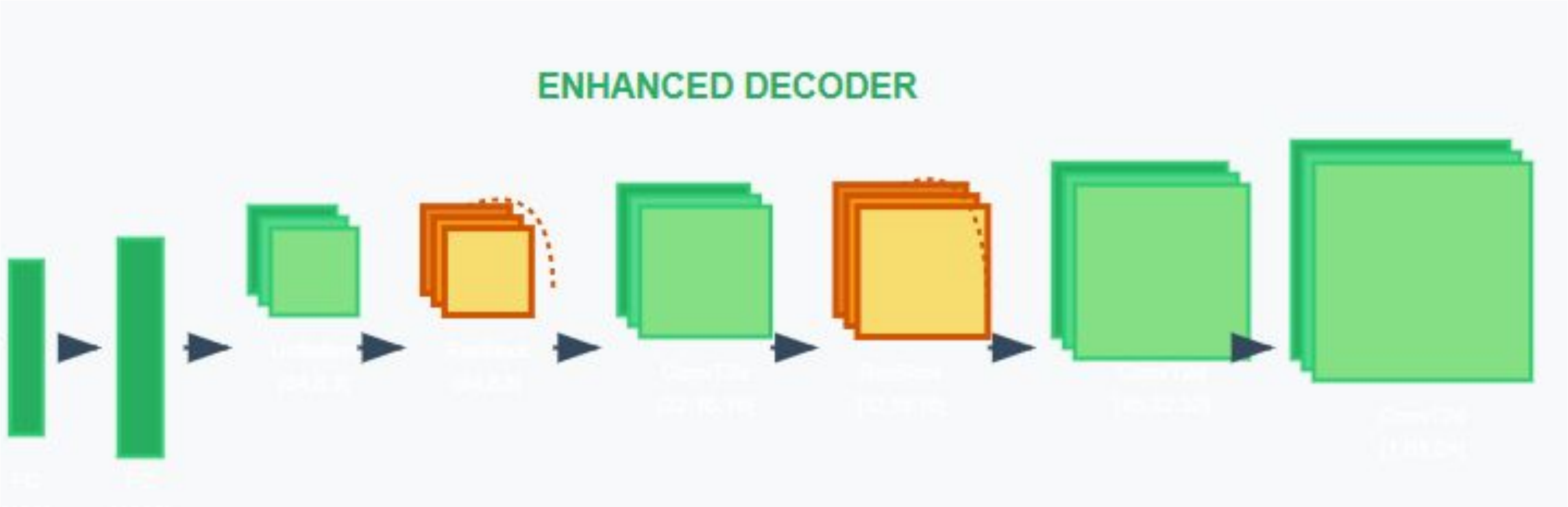
Residual blocks

Benefits of adding residual blocks:

- Enhanced feature learning
- Prevents vanishing gradients in deep networks
- Improves reconstruction quality and detail preservation



Residual blocks in the decoder

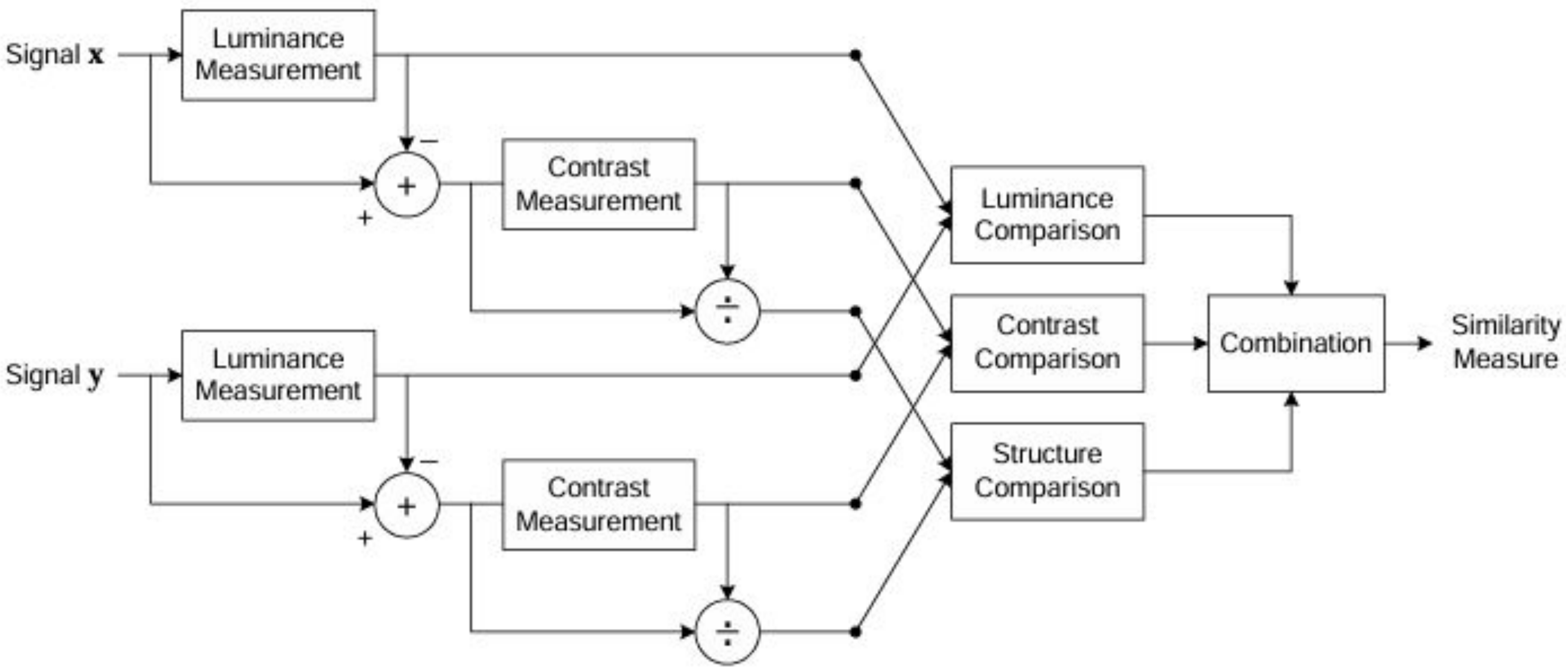


SSIM (Structural Similarity Index Measure)

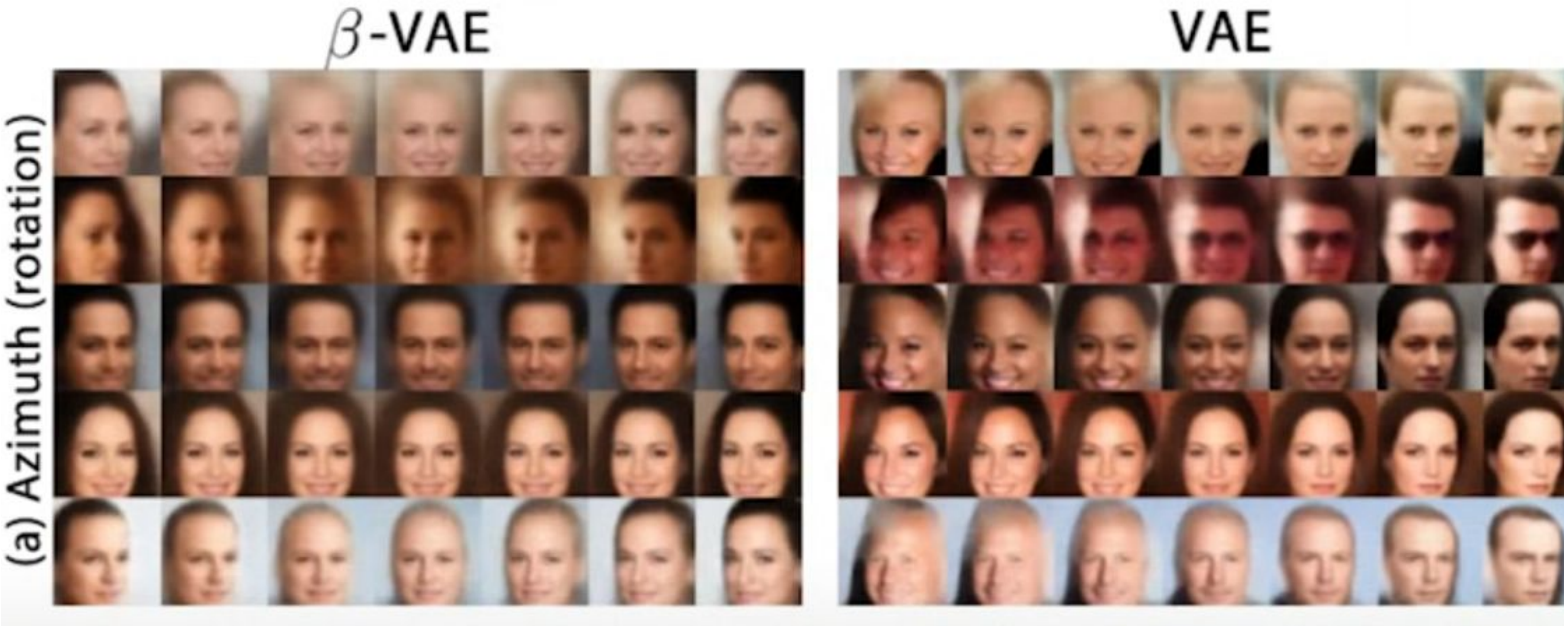
- SSIM is a perceptual loss that evaluates image similarity based on **structure**, **contrast**, and **luminance** more **aligned with human visual perception** than MSE.
- Compared to **pixel-based losses**, SSIM ensures reconstructions look realistic and diagnostically useful.
- It's used to improve the structural fidelity of generated chest X-rays, especially to preserve features like **lung edges**, which are crucial for medical diagnosis.

$$\text{Loss} = \text{Reconstruction Loss (e.g., MSE)} + \text{KL} + \lambda \cdot (1 - \text{SSIM})$$

SSIM (Structural Similarity Index Measure)



β-VAE



β-VAE regularization

- β is a hyperparameter to control the strength of the regularization term (KL divergence) in the loss function and **scales the KL divergence term** in the VAE loss:

Standard VAE Loss:

$$\mathcal{L}_{\text{VAE}} = \mathbb{E}_{q(z|x)}[-\log p(x|z)] + \text{KL}(q(z|x) \| p(z))$$

β-VAE Loss:

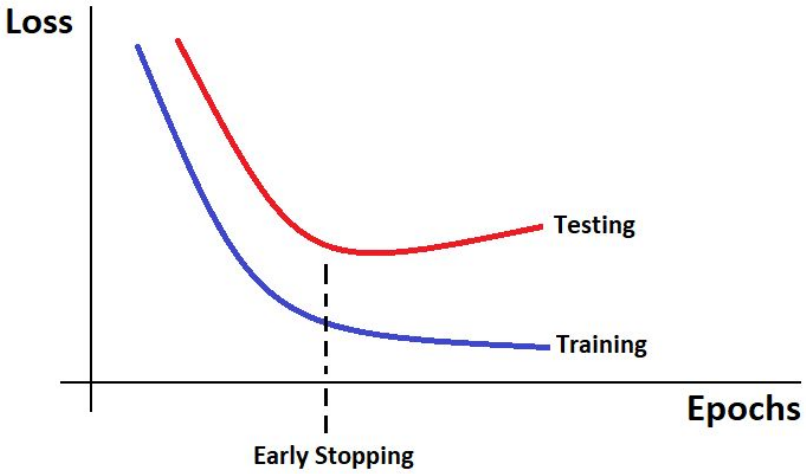
$$\mathcal{L}_{\beta\text{-VAE}} = \mathbb{E}_{q(z|x)}[-\log p(x|z)] + \beta \cdot \text{KL}(q(z|x) \| p(z))$$

- When β = 1, this is just a normal VAE.
- When β > 1, you increase pressure on the model to align the latent distribution $q(z|x)$ with the prior $p(z)$, usually a standard Gaussian.

Total Loss=Reconstruction Loss (e.g., MSE)+β *KL+λ · (1−SSIM)

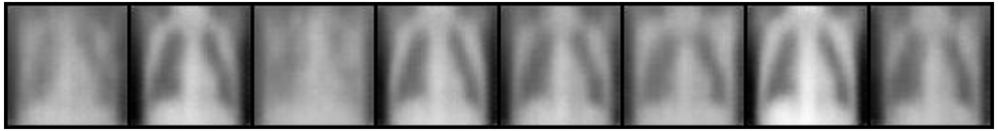
Early stopping

- Early stopping is a technique used during training to prevent overfitting and save some resources while training. It monitors the model's performance , and when performance stops improving for a specified number of epochs (patience).
- In our project we added patience = 3.

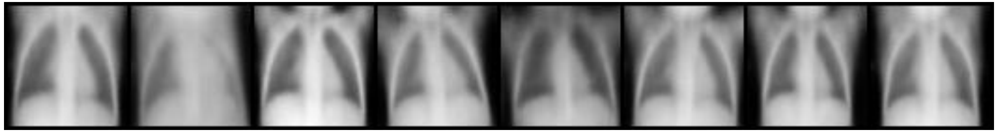


Enhanced Conditional VAE Results

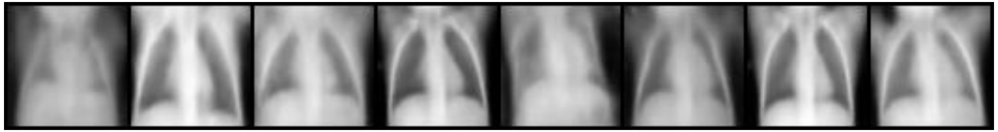
- VAE epoch 1



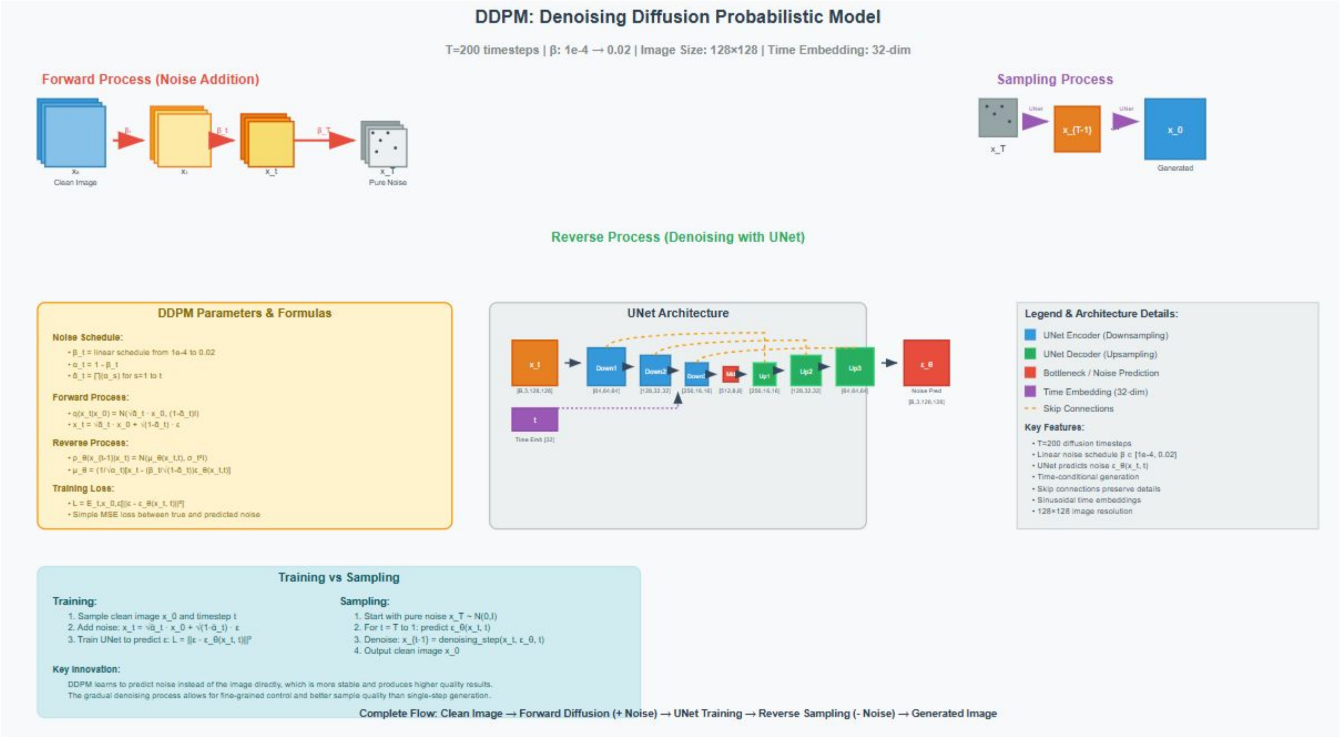
- VAE epoch 30



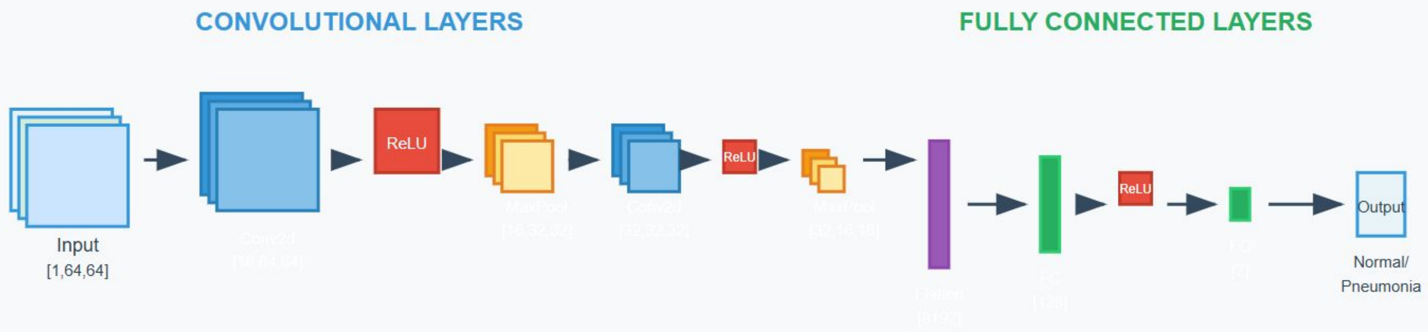
- VAE epoch 78



DDPM (Denoising Diffusion Probabilistic Model)



CNN Classifier



Dimension Flow: [1,64,64] → [16,64,64] → [16,32,32] → [32,32,32] → [32,16,16] → [8192] → [128] → [2]

Legend:

- Conv2d (3×3 kernel, padding=1)
- ReLU Activation
- MaxPool2d (2×2, stride=2)
- Flatten
- Fully Connected

Task: Binary Classification
Classes: Normal/Pneumonia

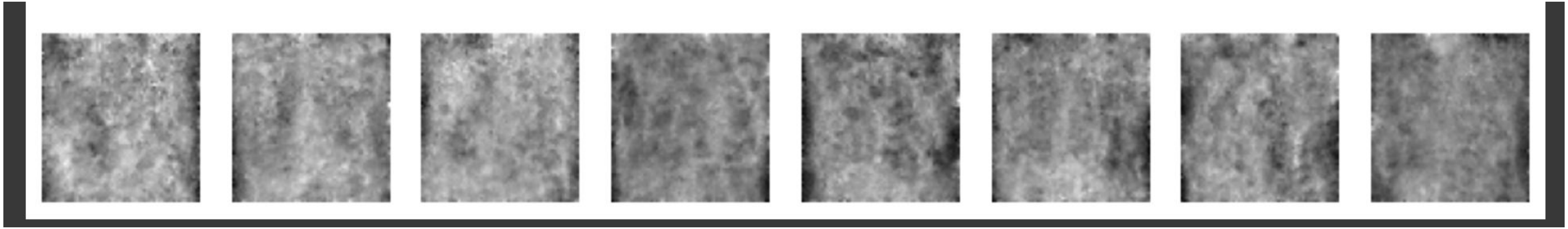
Architecture Details:

- Input: 64×64 grayscale X-ray images
- Conv1: 1→16 channels, maintains spatial size
- Conv2: 16→32 channels, maintains spatial size
- MaxPool: Reduces spatial dimensions by half
- FC1: 8192→128 neurons with ReLU
- FC2: 128→2 neurons (classification output)
- Total Parameters: ~1M parameters

Key Features:

- Simple and fast architecture
- Suitable for medical imaging
- Binary classification output
- Progressive downsampling
- ReLU activations
- Efficient parameter usage

DDMP and CNN results



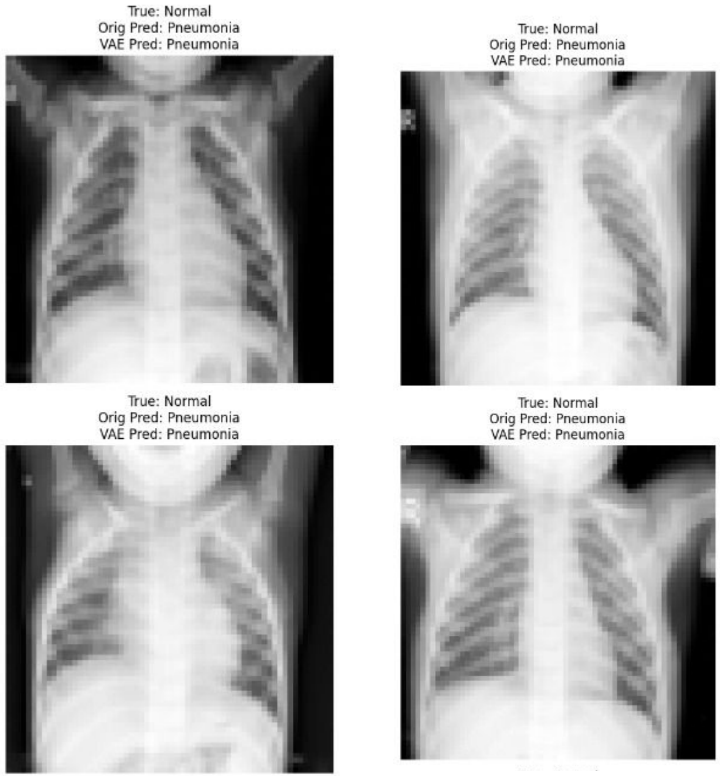
```
Epoch 1 done.
Epoch 2 done.
Epoch 3 done.
Accuracy: 0.7420
Precision: 0.7101
Recall: 0.9923
F1: 0.8278
Confusion matrix:
 [[ 76 158]
 [  3 387]]
```

To address the class imbalance in the chest X-ray dataset, we used a **DDPM (Denoising Diffusion Probabilistic Model)** to generate synthetic images of the minority class ("Normal").
These synthetic images were combined with the real data to create a more balanced training set.

We then trained a **CNN classifier** on the augmented dataset (real + DDPM synthetic) and evaluated its performance on the real test set.

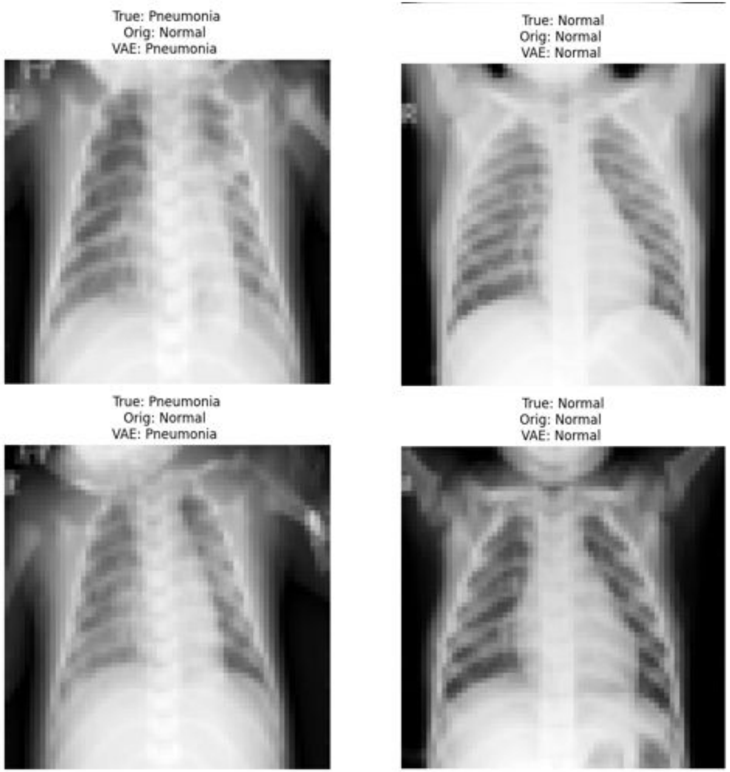
CNN classifier with VAE data

```
Training classifier on original dataset
Epoch 1/5, Loss: 0.2045
Epoch 2/5, Loss: 0.1022
Epoch 3/5, Loss: 0.0884
Epoch 4/5, Loss: 0.0681
Epoch 5/5, Loss: 0.0598
Accuracy on test set: 0.7484
Training classifier on VAE-augmented dataset
Epoch 1/5, Loss: 0.2599
Epoch 2/5, Loss: 0.1167
Epoch 3/5, Loss: 0.0811
Epoch 4/5, Loss: 0.0598
Epoch 5/5, Loss: 0.0500
Accuracy on test set: 0.7532
```



CNN classifier with Enhanced VAE data

```
Training classifier on original dataset
Epoch 1/5, Loss: 0.2057
Epoch 2/5, Loss: 0.1214
Epoch 3/5, Loss: 0.0859
Epoch 4/5, Loss: 0.0738
Epoch 5/5, Loss: 0.0624
Original Accuracy: 0.8301
Class 0 (Normal) - Precision: 0.9507, Recall: 0.5769, F1: 0.7181
Class 1 (Pneumonia) - Precision: 0.7946, Recall: 0.9821, F1: 0.8784
Training classifier on VAE-augmented dataset
Epoch 1/5, Loss: 0.2178
Epoch 2/5, Loss: 0.0868
Epoch 3/5, Loss: 0.0569
Epoch 4/5, Loss: 0.0397
Epoch 5/5, Loss: 0.0300
VAE-Augmented Accuracy: 0.7837
Class 0 (Normal) - Precision: 0.9091, Recall: 0.4701, F1: 0.6197
Class 1 (Pneumonia) - Precision: 0.7535, Recall: 0.9718, F1: 0.8488
```



Challenges & Issues Encountered

- Severe Class Imbalance
- Computational Constraints
- Small Subsets for Debugging
- Quality of Synthetic Images
- Checkerboard Artifacts
- Posterior Collapse in VAEs (If the latent space was too large or the KLD loss weight too strong, the VAE decoder produced only black or blank images.)
- Hyperparameter Tuning
- No Direct Evaluation Metrics for Generators

Thank you.