LUDWIG-
MAXIMILIANS-
UNIVERSITÄT
MÜNCHEN

Fakultät für Mathematik, Informatik und Statistik
Institut für Informatik

**Lehrstuhl für Datenbanksysteme
und Data Mining**

Anomaly Detection in X-Ray Images

Practical Course "Big Data Science"
DeepC Final Presentation
29.07.2019

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Presentation for:

deepc

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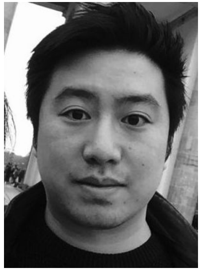

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Agenda

- Task & Data
- Preprocessing workflow
- Method & Models training
- Visualizations
- Future work

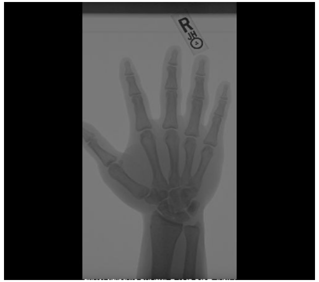
Task Allocated to Us

- Classify hand X-ray images into normal and not normal
- Because of high labelling cost → unsupervised
- Visualize problematic areas of not normal hand

Data Provided

- Subset of MURA dataset
- Contains hand X-rays grayscale images
- Very noisy

- **Size**: 5543 images
- **Percentage of positive images**: 26%
- **Number of patients**: 1964
- Approx. 10% of images are **mislabeled**.

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Legends

✅ **Implemented**: The algorithm has been implemented and included in the repository
✅ **Tested**: It has been tested
✅ **Integrated**: It has been integrated into the pipeline and evaluated

✅ **Green**: Working Fine
⚠️ **Yellow**: No major success
❌ **Red**: Skipped this step

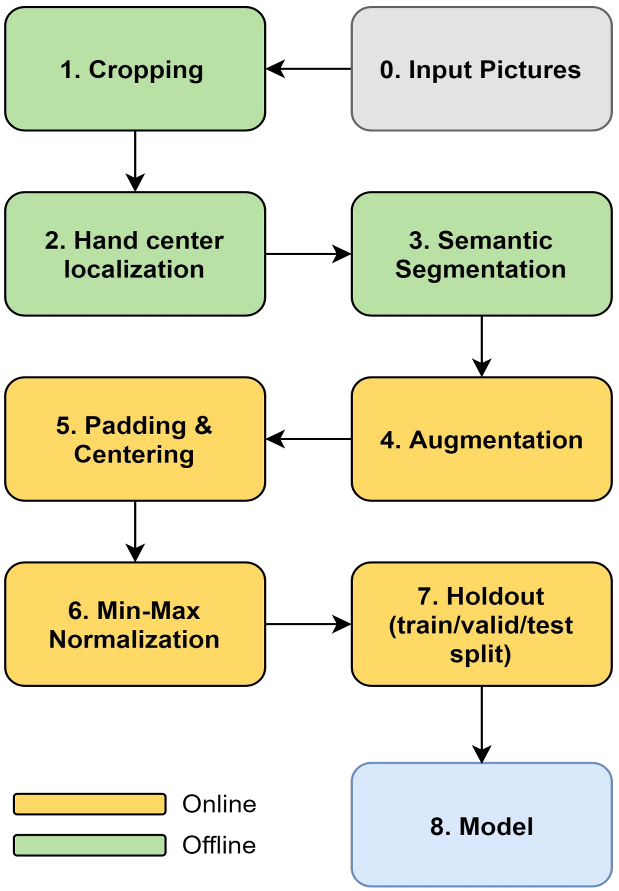
Workflow Followed

Preprocessing:

- **Cropping** using OpenCV
- **Object detection** using Tensorflow
- Semantic segmentation (Photoshop)

Learning and Prediction:

- 3 types of **Autoencoders**
- 3 types of **GANs**



Preprocessing: Square Detection

- **Idea**: Crop out X-ray-scans, synthetically created for MURA
- Based on OpenCV Contours Detection

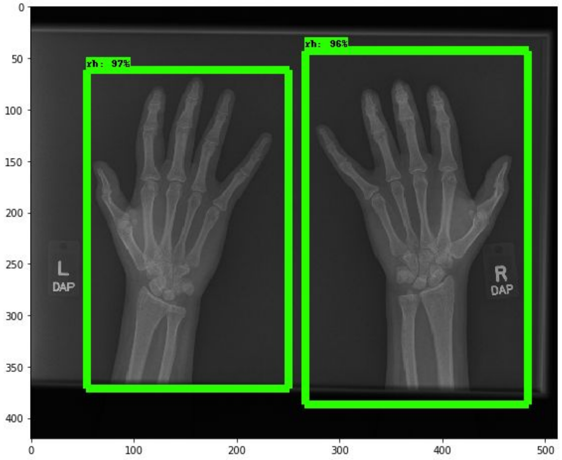
Frameworks Used:

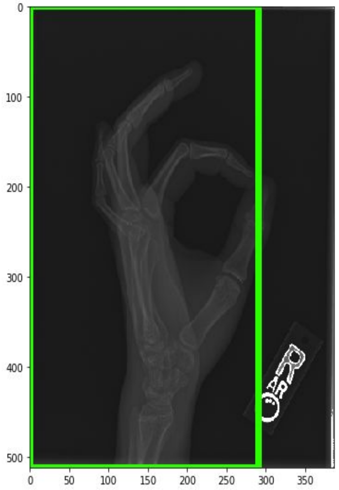
✅ OpenCV

✅ Implemented
✅ Tested
✅ Integrated

Preprocessing: Hand Detection & Cropping

- **Idea**: Detect hand and crop, output image has centered hand
- Based on **Single shot multibox detector** (SSD) with MobileNet
- Manually labeled bounding boxes for over 150 hands
- Fails for tilted images, not whole palms, two hands on one image
- Manually cropped all undetected images





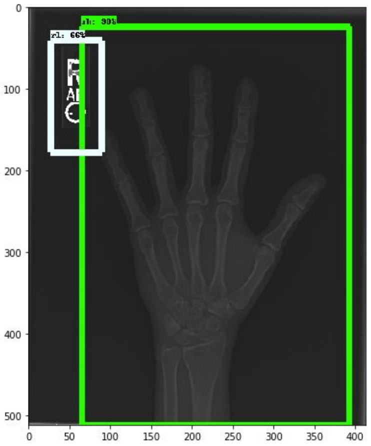
Frameworks Used:

✅ OpenCV
✅ Tensorflow object detection

✅ Implemented
✅ Tested
✅ Integrated

Preprocessing: Writings Detection & Removal

- **Idea**: Detect writings and remove by inpainting
- Analogous SSD method
- Manually labeled bounding boxes for over 100 labels
- Fails for writings, which is too close to hand, tilted writings



Frameworks Used:

✅ OpenCV
✅ Tensorflow object detection

✅ Implemented
⚠️ Tested
❌ Integrated

Preprocessing: Semantic Segmentation

- **Idea**: Segment hand and background, remove background
- DL Semantic segmentation requires labeled masks
- Tried with **GrabCut**, but it is hard to adapt it for all images
- We used Photoshop **‘Select Subject’** option
- Still not perfect solution

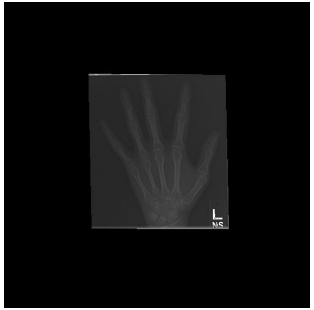
Frameworks Used:

✅ Photoshop batch processing




⚠️ Implemented
✅ Tested
✅ Integrated

Preprocessing: Augmentation



Frameworks Used:

✅ OpenCV
✅ imgaug

Augmentation techniques:
- Flipping
- Rotating
- Brightness adjustment
- Zoom in/out

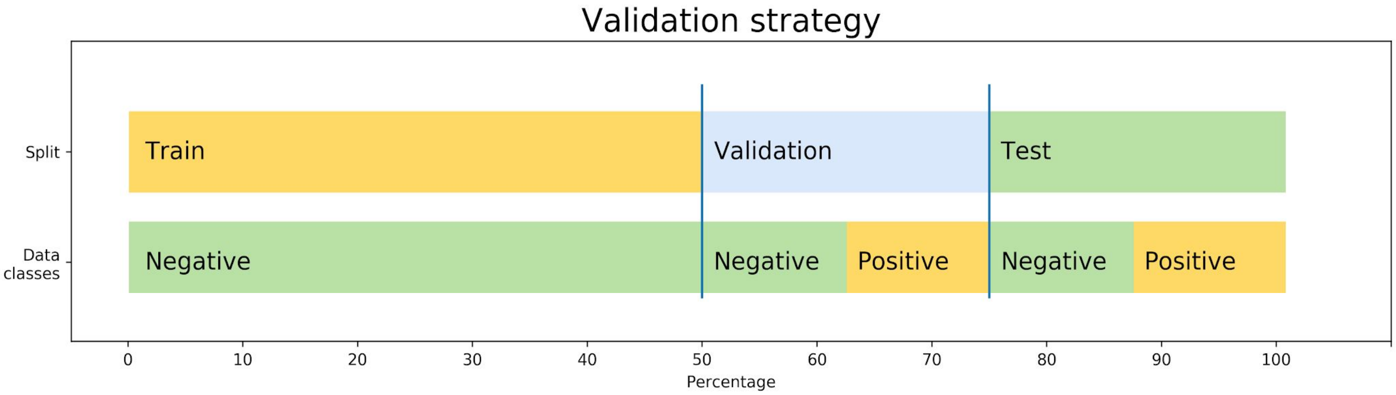
✅ Implemented
✅ Tested
✅ Integrated

Processing: Data-split

- Unsupervised fashion means that we use only normal images in a training phase
- Still need to know, that images are normal
- Train is only 50% - to make test and validation balanced

Frameworks Used:

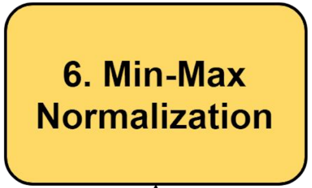
✅ Scikit-learn

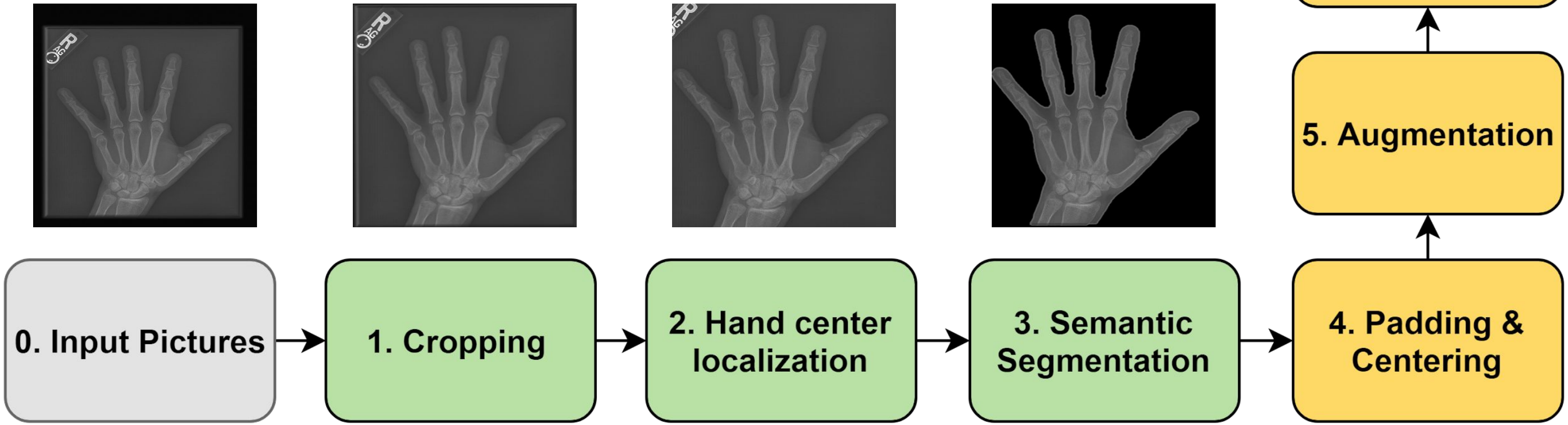


✅ Implemented
✅ Tested
✅ Integrated

Preprocessing Pipeline: Altogether

- **Centered Padding** converts all images to 512x512 shape (also tried uniform padding)
- **Min-Max Normalisation** scales all pixels to [0, 1]





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Method: Outlier Detection

We discriminate between **normal** and **abnormal** cases using the following statistics (outlier scores):

- Reconstruction loss (CAE, BiGAN, Alpha-GAN)
- Reconstruction loss + Kullback-Leibler divergence (VAE)
- Discriminator output probability (DCGAN, BiGAN, Alpha-GAN)
- Latent features outlier detection:
    - One-class SVM (CAE)
    - DBSCAN (CAE)

Training: Overview

- **Unsupervised Learning:**
  - Non-negative matrix factorisation + DBSCAN / One-Class SVM
- **Unsupervised Deep Learning:**
  - Deep One-Class Classification
  - Convolutional Autoencoder (CAE)
  - Variational Convolutional Autoencoder (VAE)
  - Deep Convolutional GAN (DCGAN)
  - Bidirectional GAN (BiGAN)
  - Alpha-GAN (GAN + VAE)

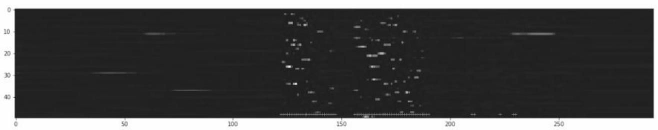
Training: Static Methods

Non Negative Matrix Factorisation:

An image V is factorized in W and H matrices

$$V(m \times n) = W(m \times p) \bullet H(p \times n)$$

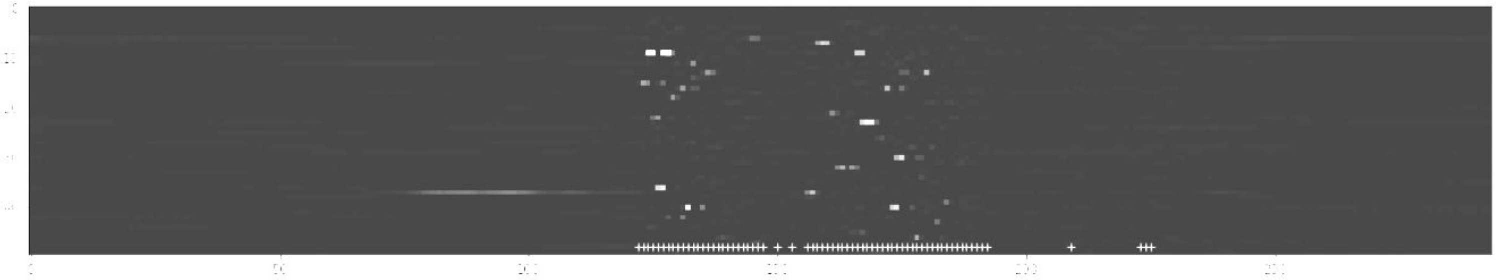
V



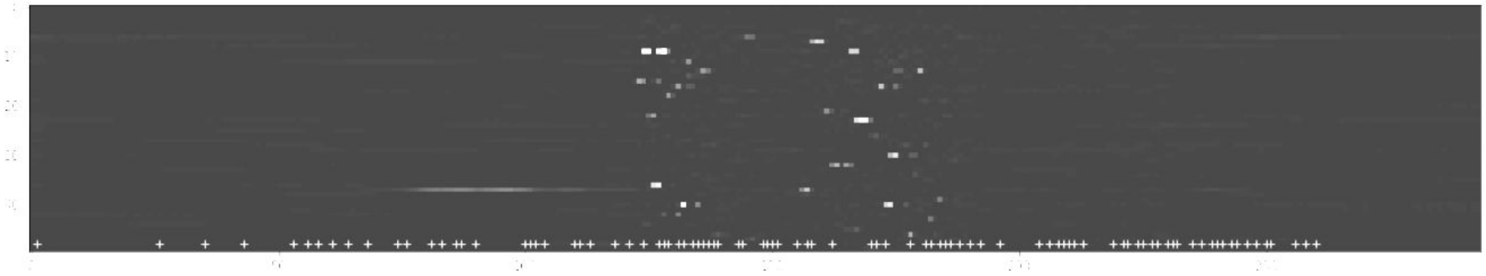
W and H looks like this

V = W • H

Training: Static Methods



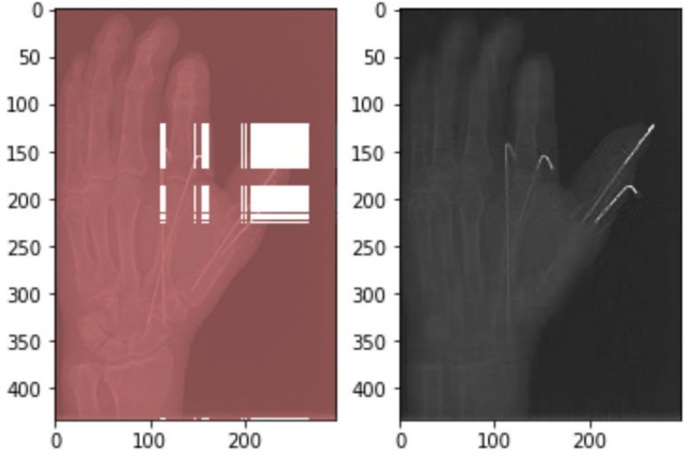
DBScan

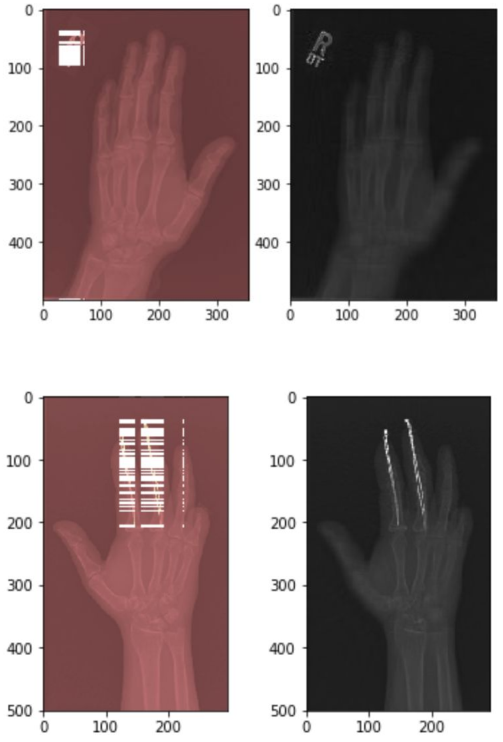


One Class SVM

Training: Static Methods

Reconstruction





Frameworks Used:

✅ OpenCV
✅ Scikit-learn

✅ Implemented
⚠️ Tested
❌ Integrated

Training: Deep One-Class Classification

- Predicts **score** for an image
- **Higher the score, higher the abnormality**
- Completely unsupervised
- Not a single label needed for training
- It however **requires an outlier classes**
- For example, to train the model for hand images, we need images of non-hands, like legs, chest, etc, which is fairy easy and cheap to obtain

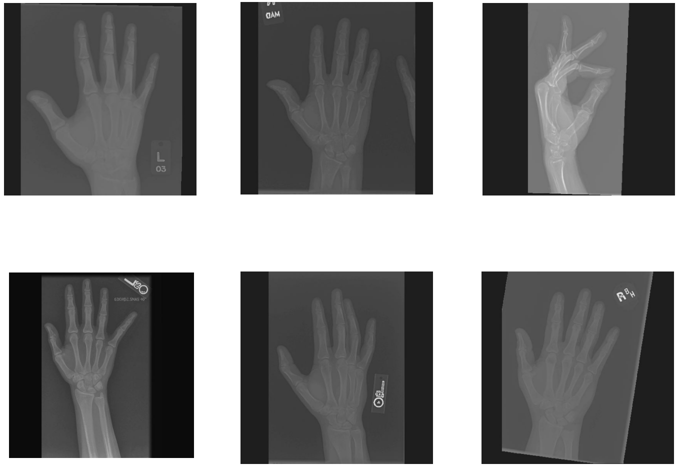
Frameworks Used:

✅ OpenCV
✅ Tensorflow

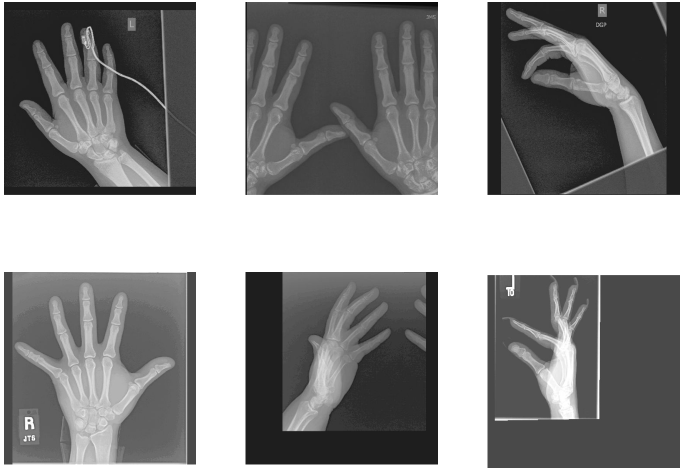
✅ Implemented
⚠️ Tested
⚠️ Integrated

Training: Deep One-Class Classification

Low Score Samples:



High Score Samples:



Training: Convolutional Autoencoder

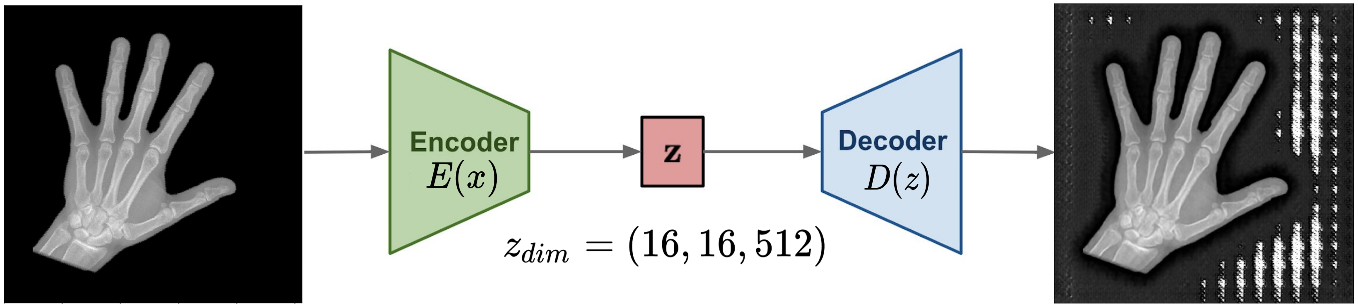
Loss: Masked Reconstruction MSE (calculated only on non-zero parts)

Outlier score: Masked MSE / Top-K SE

Best ROC-AUC: 0.58

Frameworks Used:

✅ OpenCV
✅ PyTorch



$x_{dim} = (512, 512, 1)$ $x_{dim} = (512, 512, 1)$

✅ Implemented
✅ Tested
✅ Integrated

Training: Bottleneck Convolutional Autoencoder

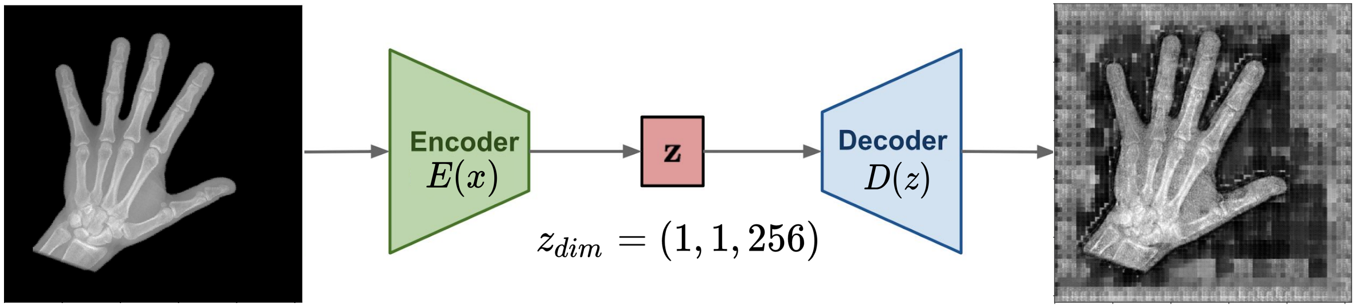
Loss: Masked Reconstruction MSE (calculated only on non-zero parts)

Outlier score: Masked MSE / Top-K SE

Best ROC-AUC: 0.57

Frameworks Used:

✅ OpenCV
✅ PyTorch

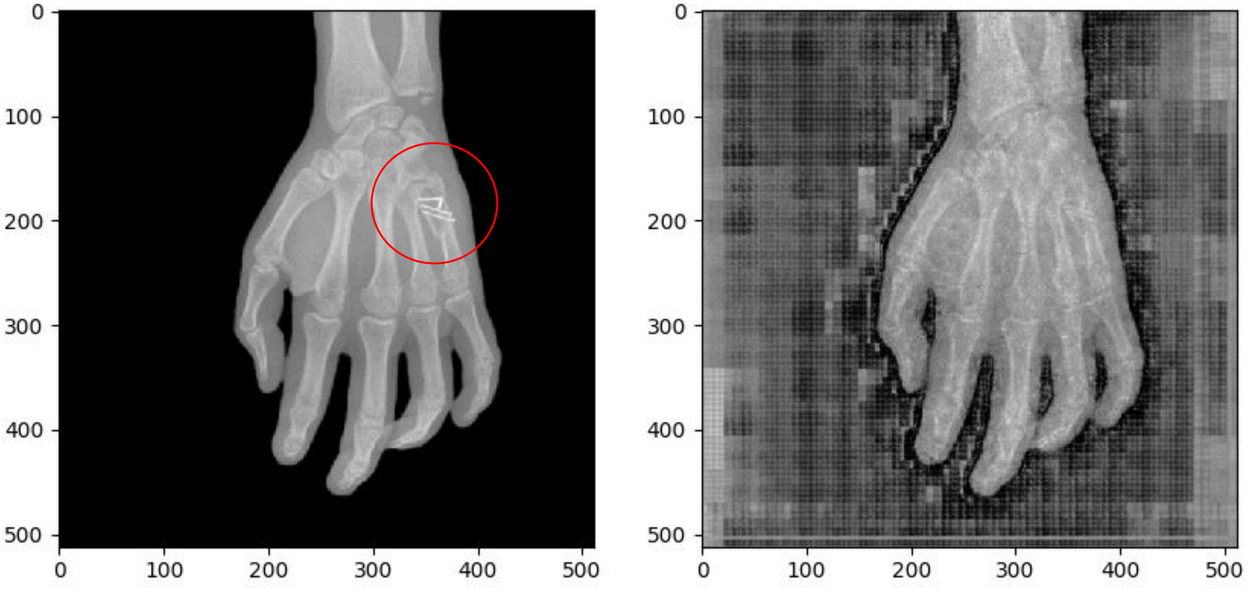


$x_{dim} = (512, 512, 1)$ $x_{dim} = (512, 512, 1)$

✅ Implemented
✅ Tested
✅ Integrated

Training: Bottleneck Convolutional Autoencoder

Epoch 73: Not reconstructing extrinsic objects → A way to detect them



Training: Variational Autoencoder

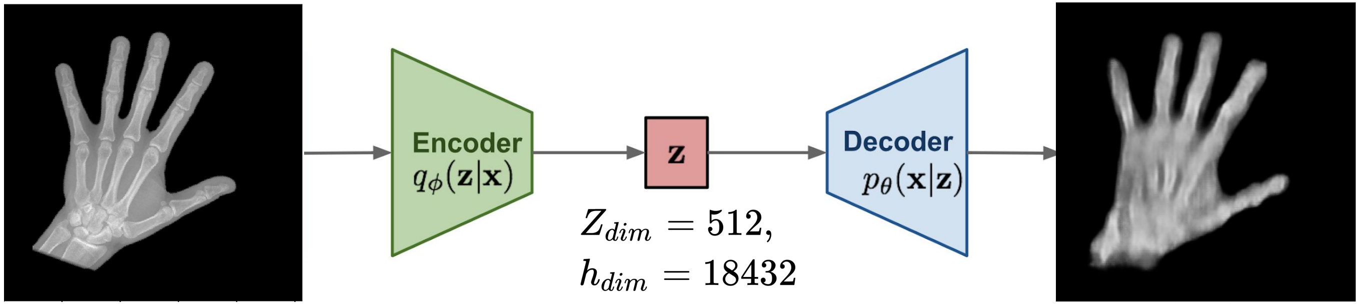
Loss: Binary Cross Entropy (Pixelwise) + Kullback Leibler Divergence (Latent features)

Outlier score: Loss, used for training

Best ROC-AUC: 0.53

Frameworks Used:

✅ OpenCV
✅ PyTorch



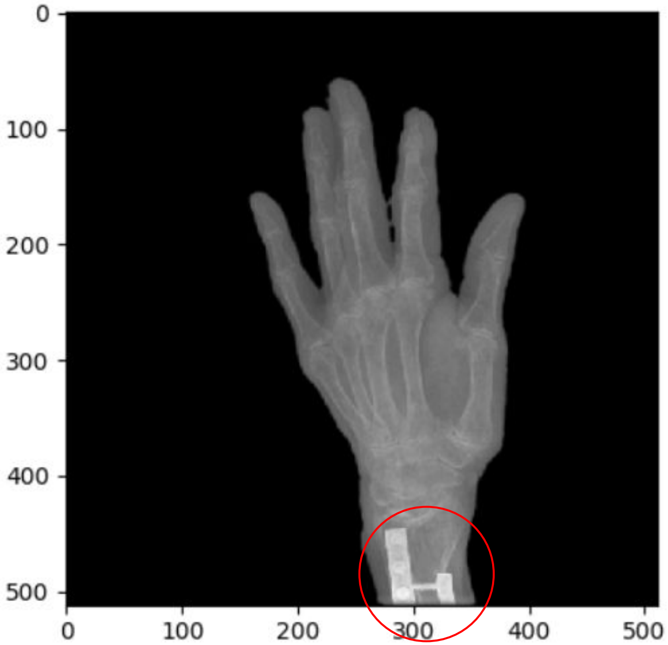
$x_{dim} = (512, 512, 1)$ $x_{dim} = (512, 512, 1)$

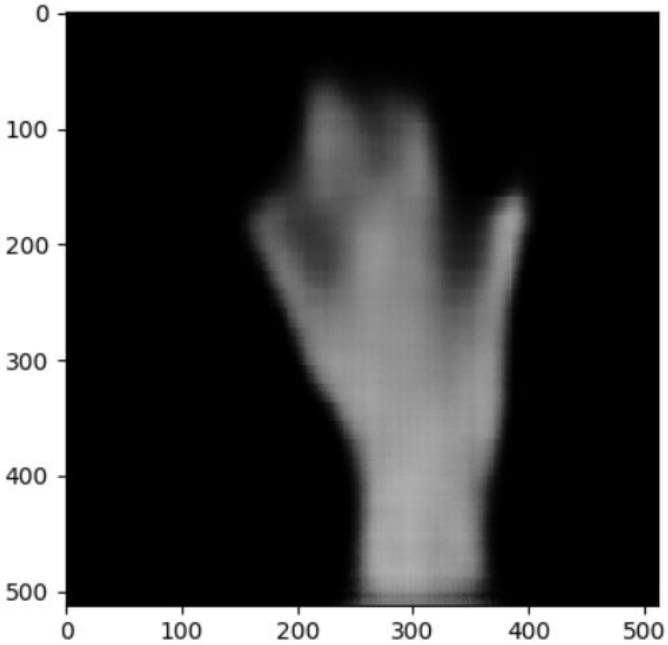
Epoch 600

✅ Implemented
✅ Tested
✅ Integrated

Training: Variational Autoencoder

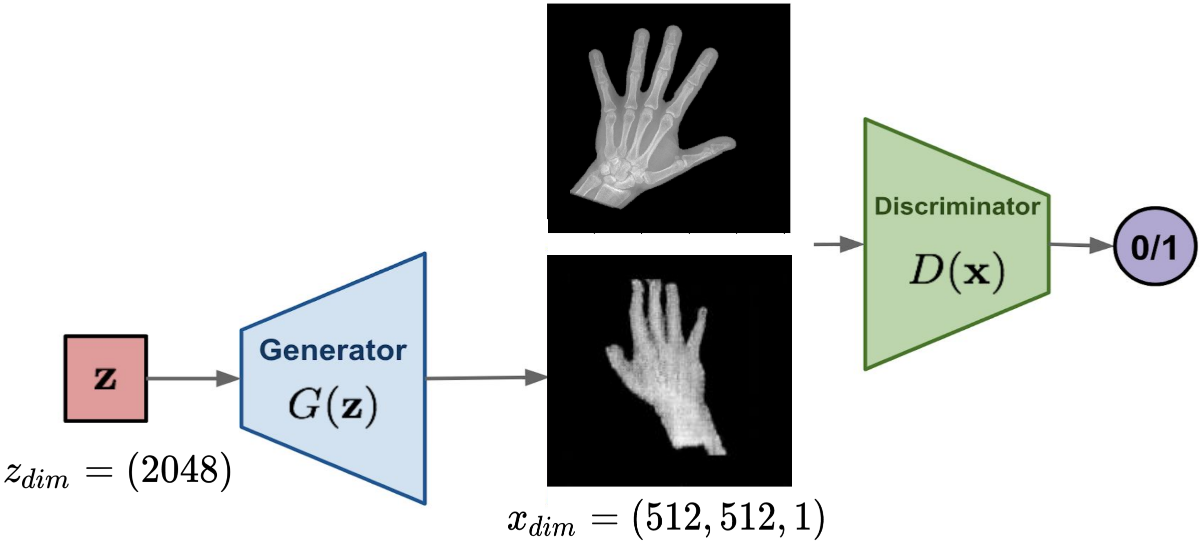
Epoch 17: Not reconstructing obvious anomalies → A way to detect them





Training: Deep Convolutional GAN

Loss: Binary Cross Entropy between fake and real images
Outlier score: Discriminator output probability
Best ROC-AUC: 0.57



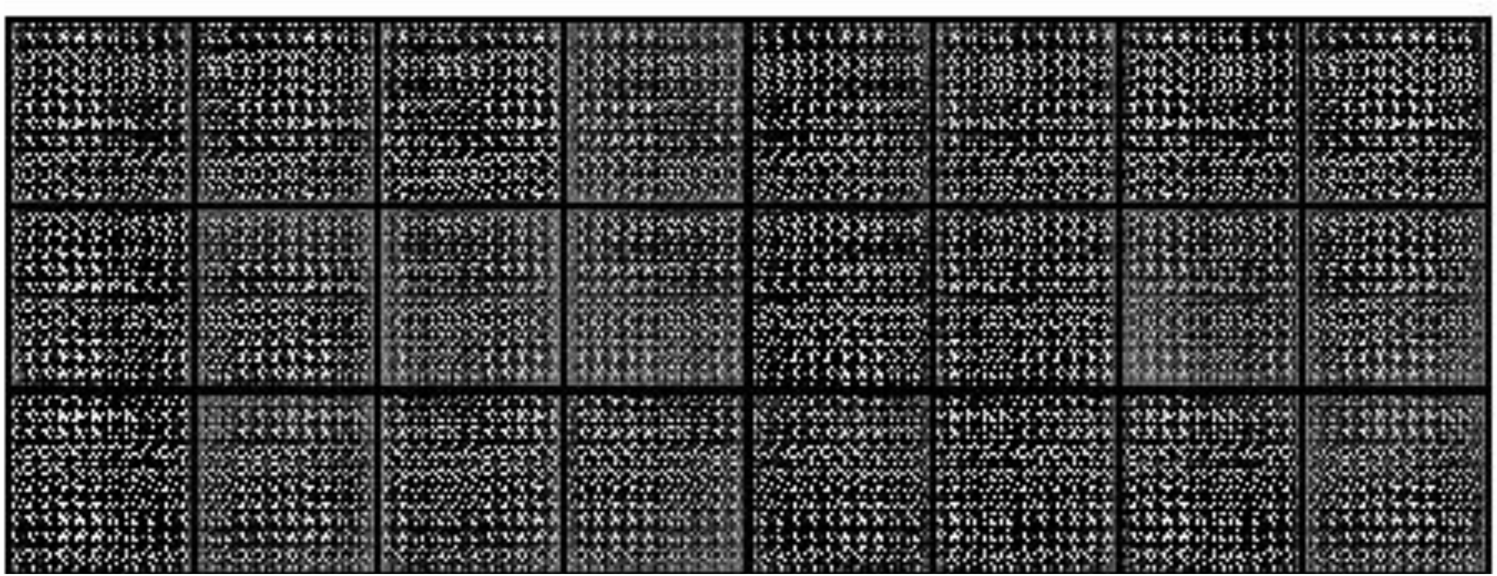
Frameworks Used:

✅ OpenCV
✅ PyTorch

✅ Implemented
✅ Tested
✅ Integrated

Training: Deep Convolutional GAN

- Hard to choose learning rates
- Often - mode collapse (sacrifice diversity on accuracy)



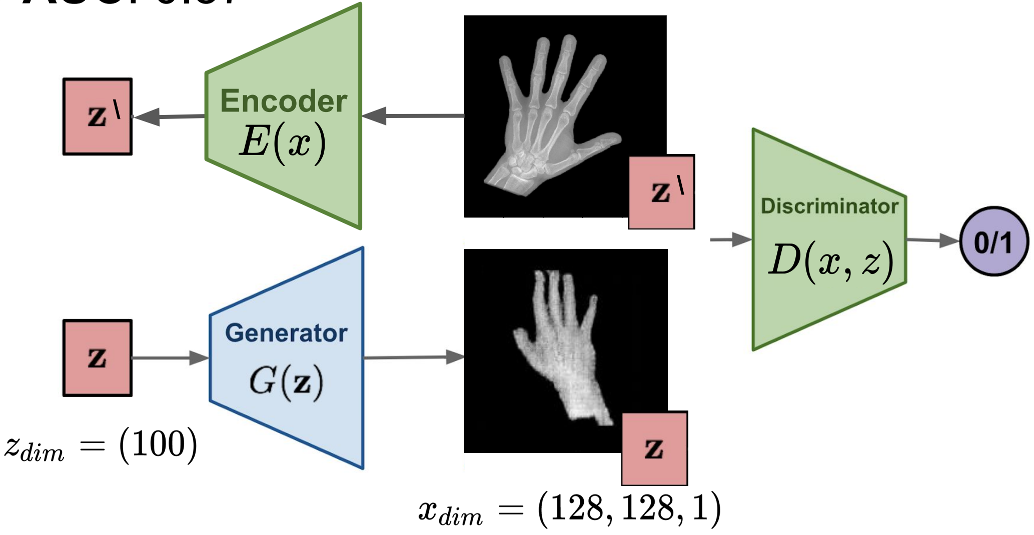
Training: Bidirectional GAN

Loss: Binary Cross Entropy between fake and real images

Added self-attention layer

Outlier score: Discriminator output probability / Masked MSE

Best ROC-AUC: 0.57



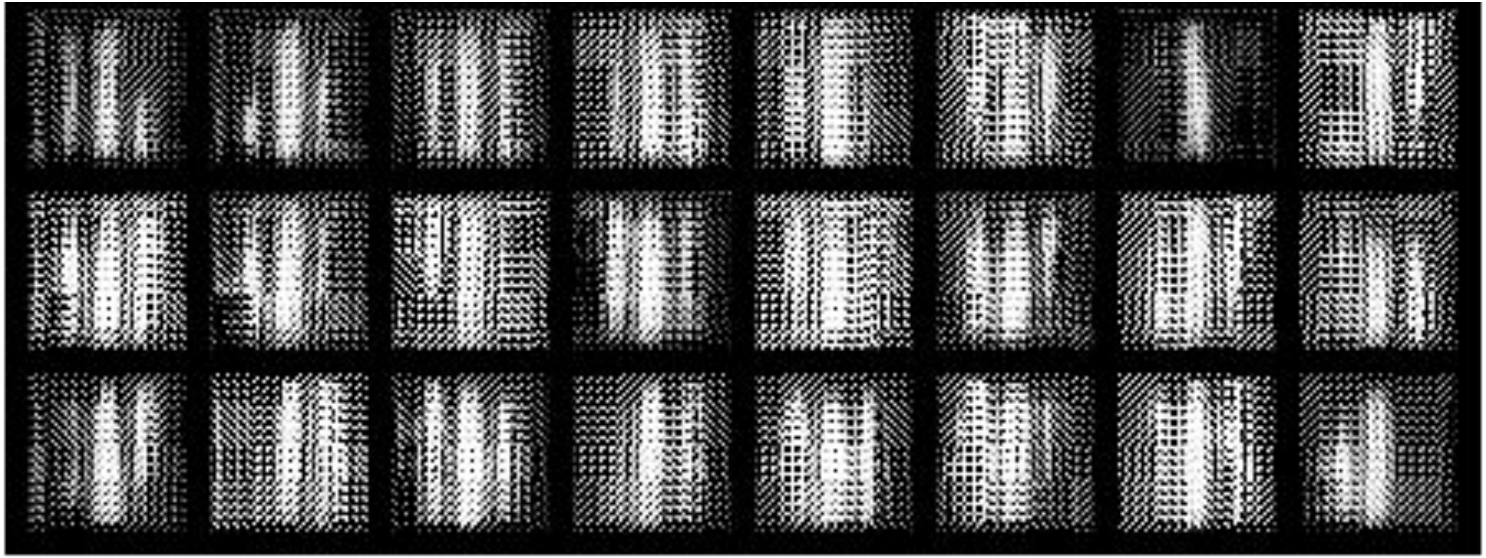
Frameworks Used:

✅ OpenCV
✅ PyTorch

✅ Implemented
✅ Tested
✅ Integrated

Training: Bidirectional GAN

- Better in reconstruction
- Often - mode collapse (sacrifice diversity on accuracy)



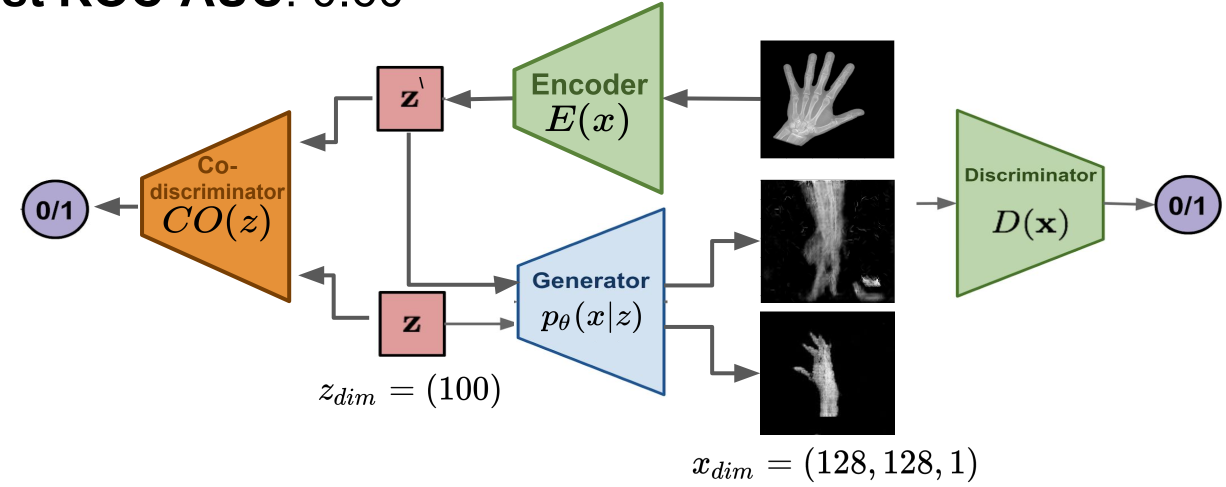
Training: Alpha-GAN

Loss: Binary Cross Entropy between fake/reconstructed and real images + Kullback Leibler Divergence (Latent features)

Added self-attention layers

Outlier score: Discriminator output probability / Masked MSE

Best ROC-AUC: 0.60



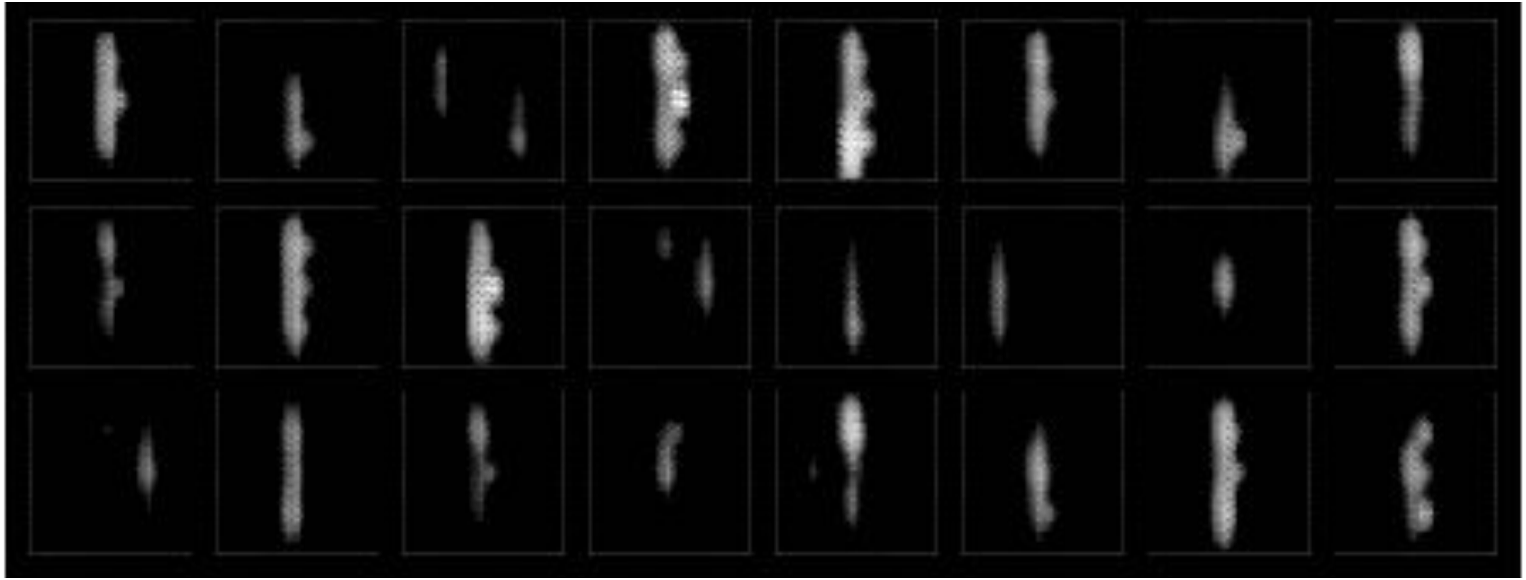
Frameworks Used:

- ✅ OpenCV
- ✅ PyTorch

- ✅ Implemented
- ✅ Tested
- ✅ Integrated

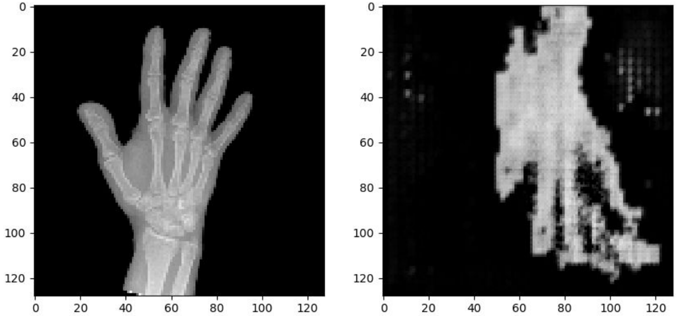
Training: Alpha-GAN

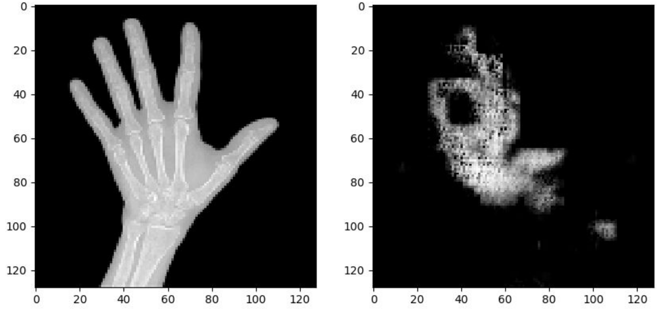
- Worse in reconstruction (hard to choose learning rate)
- Generator outputs more diverse images

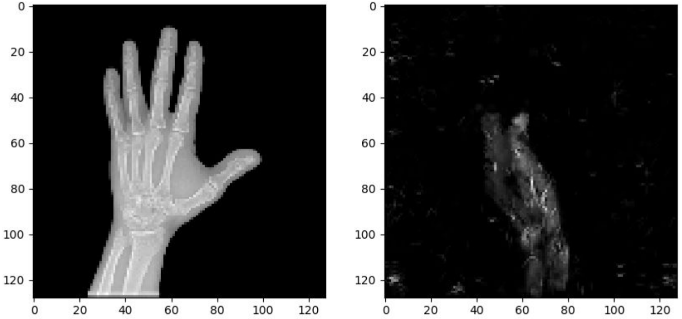


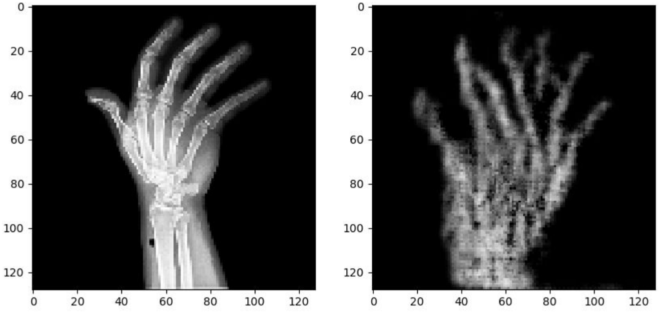
Training: BiGAN & Alpha-GAN

- Main problem: not diverse generator → hard to use RMSE for outlier score









Comparison of Autoencoders and GANS

	Unmasked Images	Masked Images	
Model	ROC-AUC	ROC-AUC	APS
CAE (z_{dim} = (512, 16, 16))	0.45	0.58	0.58
CAE (z_{dim} = (256, 1, 1))	0.44	0.57	0.58
VAE	0.50	0.53	0.57
DCGAN	**0.57**	0.56	0.63
BiGAN	-	0.57	**0.66**
Alpha-GAN	-	**0.60**	**0.66**

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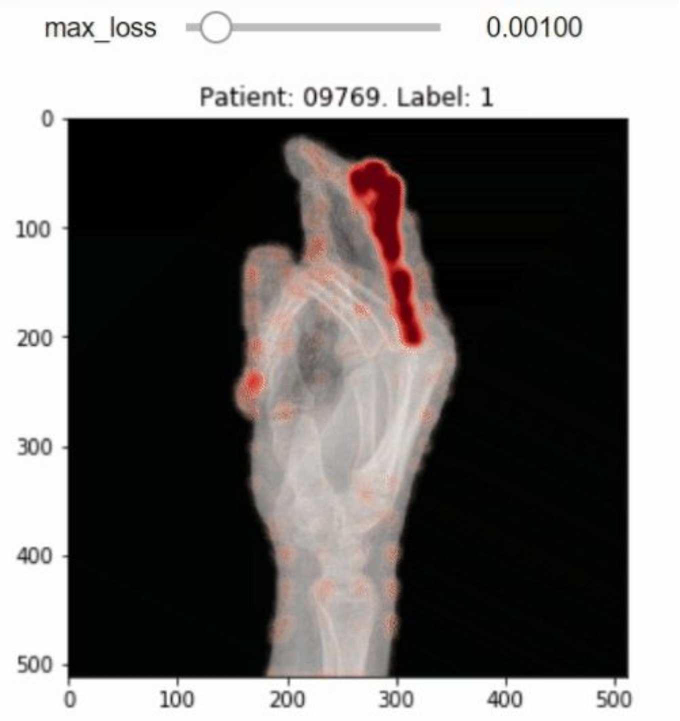
Pixelwise Loss for Visualisation: Abnormal hands

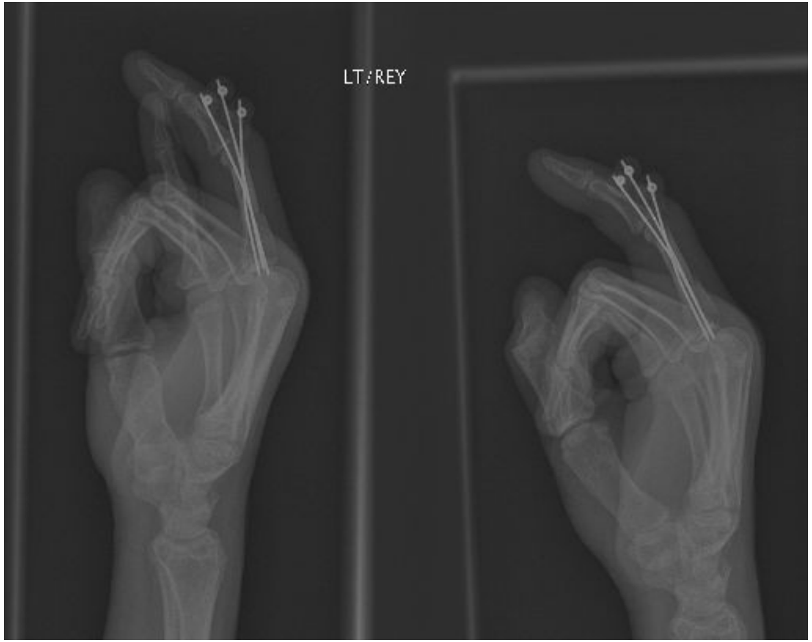
- Possible for Convolutional Autoencoders



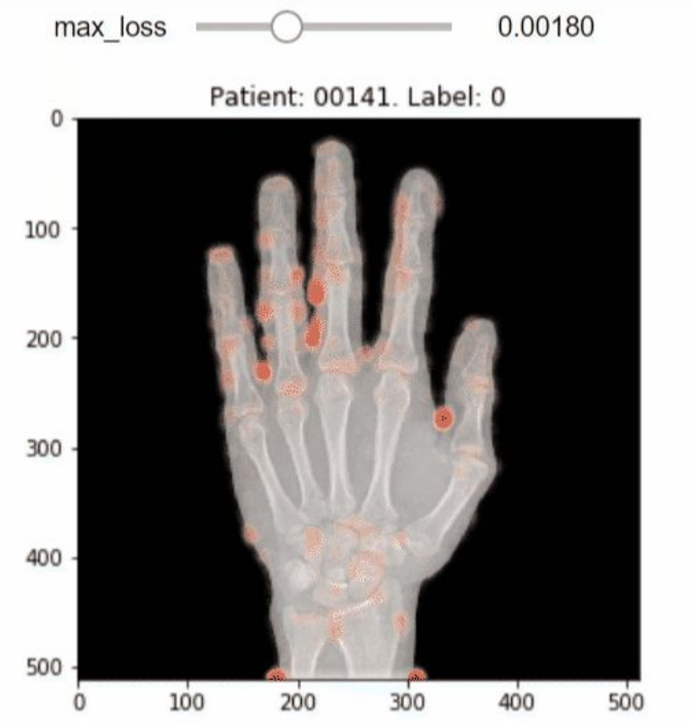
Pixelwise Loss for Visualisation: Normal Hand

Pixelwise Loss for Visualisation: Abnormal hand





Pixelwise Loss for Visualisation: Normal Hand



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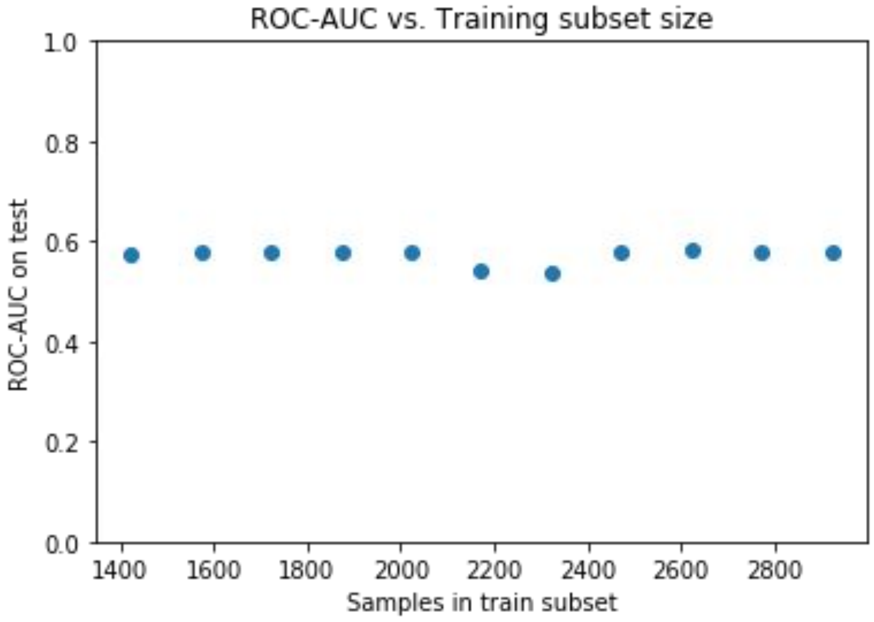
Extension Possibilities

- Flexible and generic architecture
- Can be extended for other body parts with slight modifications
- For example:
    - Object detection model can be extended to detect other parts and redirect the flow to corresponding neural network
    - New autoencoders can be trained and saved to find anomalies in other type of data sets

Extension Possibilities: Quantity vs. Quality

- Extension of training subset does not increase performance
- **Quality matters:** need to develop more sophisticated data-cleaning pipeline



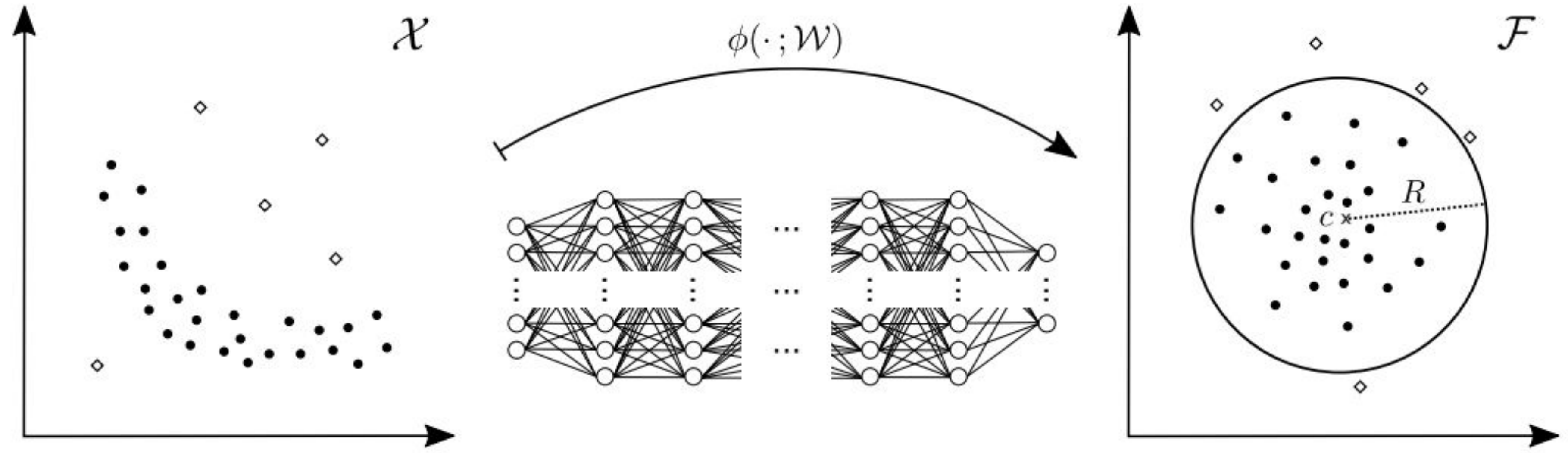
Future Work

- Evaluate the usage of **flow-based models**
- Visualize **attention maps** for Self-Attentive GANs
- **Image pipeline improvements:**
  - Few-shot semantic segmentation for hand masking
  - Tuning of hand detector
  - Median filters evaluation
- **Models hyperparameters tuning:**
  - Learning rates adjustments, learning rate schedulers
  - Model architecture tuning

Thank You for the attention

Feedback and Questions?

Appendix: Deep One Class Classification



Appendix: Finding anomaly in encoded representation

For the initial image one the left
Encoded representation somewhat
looks like the image below.

+ represents the possible outliers as
detected by One-Class SVM algorithm

Frameworks Used:

✅ OpenCV
✅ Tensorflow
✅ Scikit

⚠️ Implemented
❌ Tested
❌ Integrated