Reference Algorithm for Anomaly Localization using MVTech Dataset

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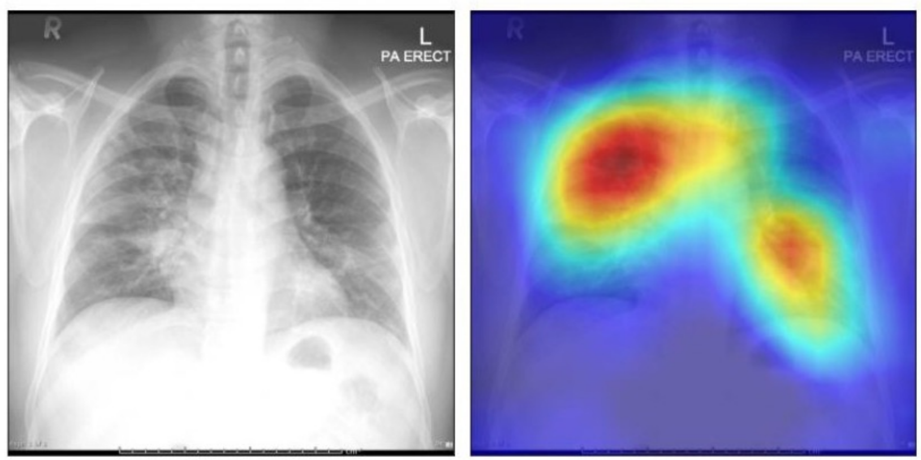
Motivation

- **Anomaly Localization**: to Identify unusual cases in images
- **Use Cases**: Industrial Application, Medical Imaging, Surveillance



COVID-19 Positive X-ray with Grad-CAM.
Grad-CAM visualises which details the model focuses on to make a decision.
Case courtesy of Dr Salah Aljilly, Radiopaedia.org, rID: 76145

Existing Methods

- Conventional Methods:
  - Feature Vectors modeled by GMM
- Deep Learning Methods (Unsupervised):
  - Autoencoder as denoising [1]
  - Image Reconstruction:
    - Convolutional Autoencoders
    - Train GANs [2], Synthetic Anomalies [3] and then Pixel-wise comparison and Thresholding (Requires class-specific threshold)

[1] Dimokranitou, A.: Adversarial autoencoders for anomalous event detection in images. Ph.D. thesis (2017)
[2] Akcay, S., A., Breckon, T.P.: GANomaly: Semisupervised anomaly detection via adversarial training. In: Asian Conference on CV. pp. 622{637. Springer (2018)
[3] Zenati, H., Foo, C.S., Lecouat, B., Manek, G., Chandrasekhar, V.R.: Efficient GAN-based anomaly detection. arXiv preprint arXiv:1802.06222 (2018)

OBJECTIVE

- Unsupervised localization of Anomalies in Images using Autoencoders and GAN

Convolutional Adversarial Variational Autoencoder With Guided Attention (CAVGA)

Attention Guided Anomaly Localization in Images

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Abstract. Anomaly localization is an important problem in computer vision which involves localizing anomalous regions within images with applications in industrial inspection, surveillance, and medical imaging. This task is challenging due to the small sample size and pixel coverage of the anomaly in real-world scenarios. Most prior works need to use anomalous training images to compute a class-specific threshold to localize anomalies. Without the need of anomalous training images, we propose Convolutional Adversarial Variational autoencoder with Guided Attention (CAVGA), which localizes the anomaly with a *convolutional latent variable* to preserve the spatial information. In the unsupervised setting, we propose an *attention expansion loss* where we encourage CAVGA to focus on all normal regions in the image. Furthermore, in the weakly-supervised setting we propose a *complementary guided attention loss*, where we encourage the attention map to focus on all normal regions while minimizing the attention map corresponding to anomalous regions in the image. CAVGA outperforms the state-of-the-art (SOTA) anomaly localization methods on MVTec Anomaly Detection (MVTAD), modified ShanghaiTech Campus (mSTC) and Large-scale Attention based Glaucoma (LAG) datasets in the unsupervised setting and when using only

Proposed Technique

- VAE-GAN with AdaCos Loss Function
  - Total Loss = VAE loss + Adversarial Loss + AdaCos Loss

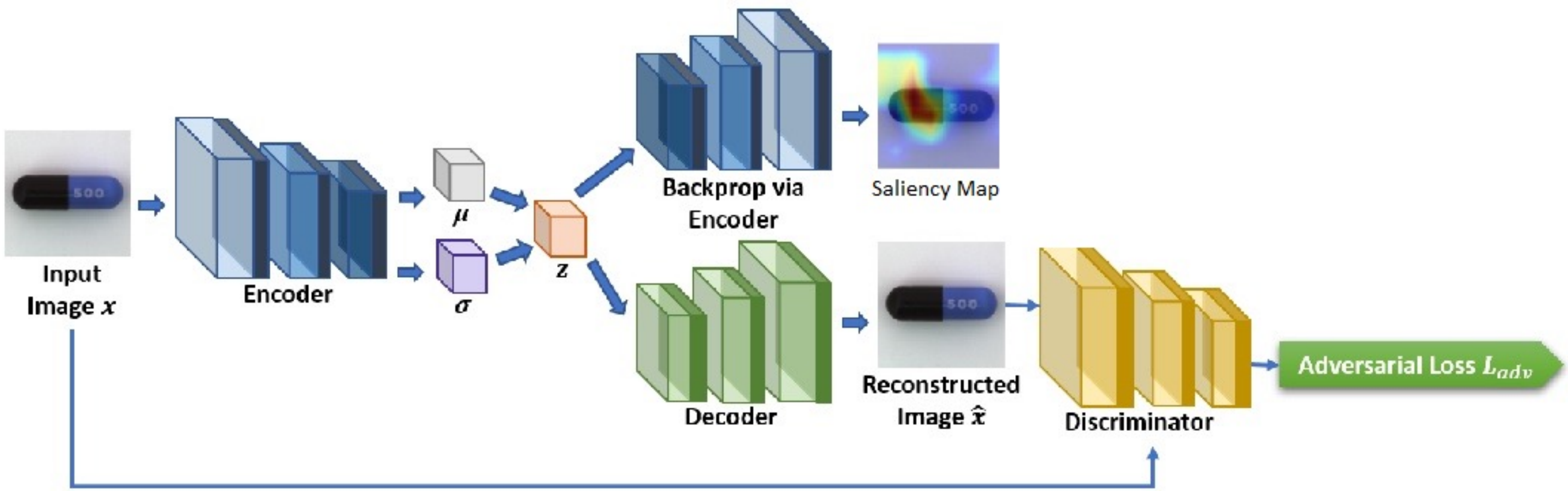


Figure 3: Unsupervised framework of VAE-GAN with Similarity Metric. (Figure taken from [1])

[1] S. Venkataramanan, Kuan-Chuan Pengy, Abhijit Mahalanobis, Attention Guided Anomaly Localization in Images, July 2020

Variational AutoEncoder

Loss Function:

$$L = L_R(x, \hat{x}) + KL(q_\phi(z|x)||p_\theta(z|x))$$

Reconstruction loss is:

$$L_R(x, \hat{x}) = -\frac{1}{N}\sum_{i=1}^{N} x_i \; log \; \hat{x}_i + (1-\hat{x}_i)\, log(1-\hat{x}_i)$$

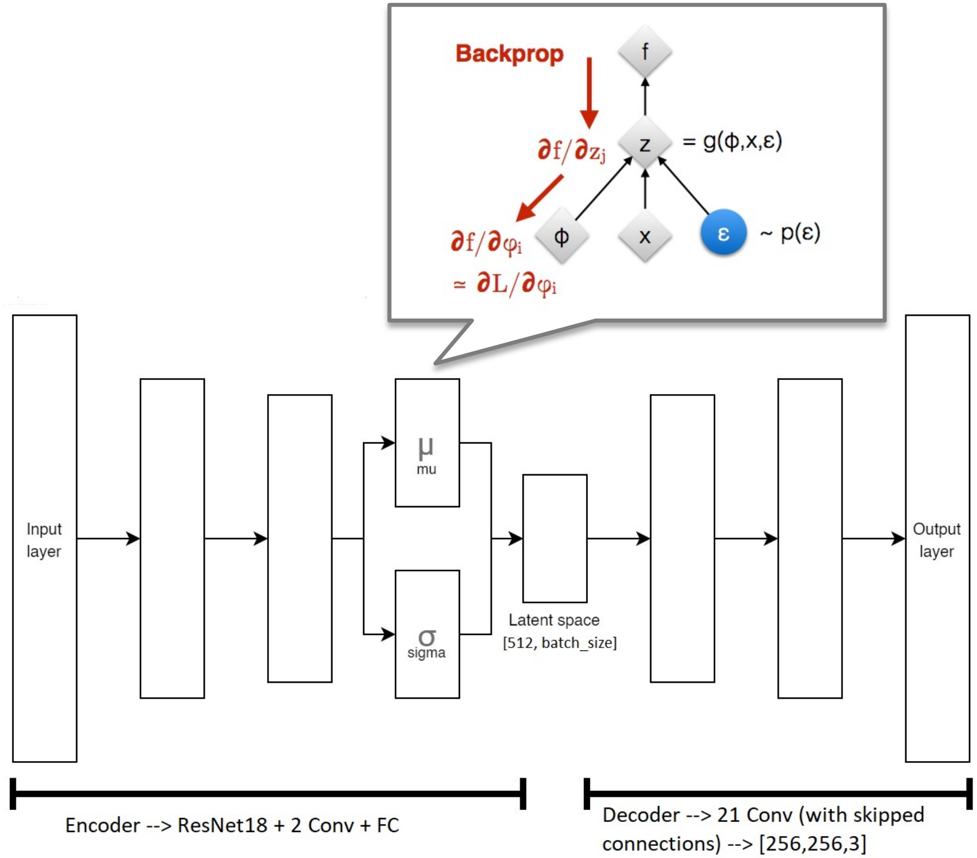


Figure 4: Variational Autoencoder with Reparameterization Trick [1]

[1] Kingma, D.P., Welling, M.: Auto-encoding variational bayes. In: International Conference on Learning Representations (2014)

Generative Adversarial Network

- Discriminator to improve sharper reconstructed $\hat{x}$ images
- Adversarial Learning can be formulated as:

$$L_{adv} = -\frac{1}{N}\sum_{i=1}^{N} \log(D(x_i)) + log(1 - D(\hat{x}_i))$$

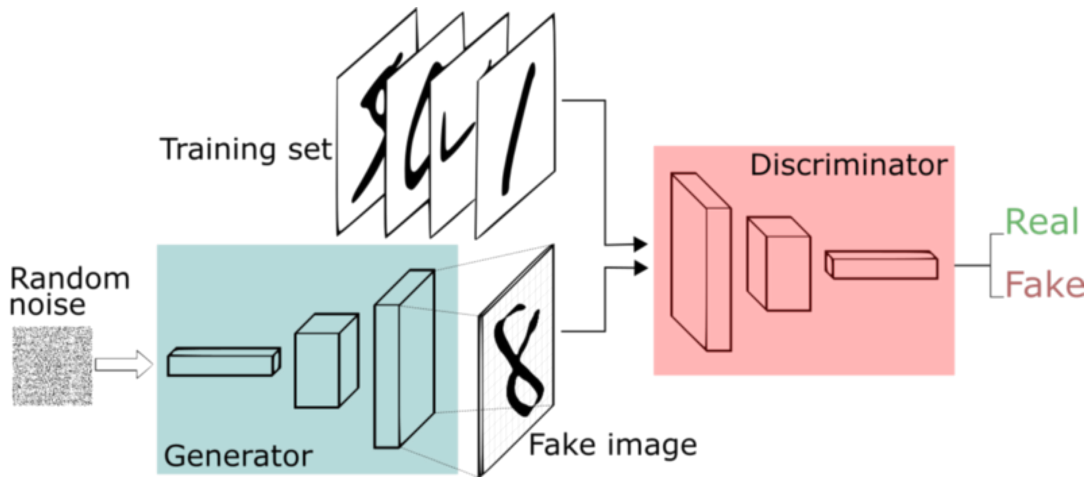
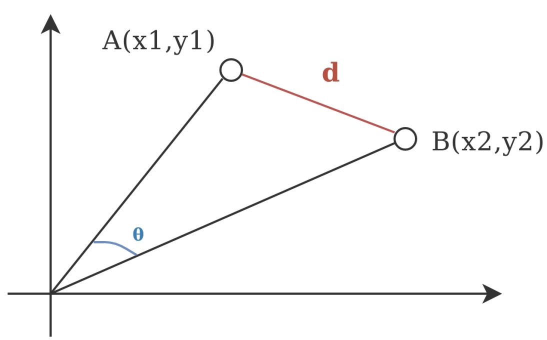


Figure 5: Generative Adversarial Network
(Figure taken from [1])

[1] Thalles Silva, An intuitive introduction to Generative Adversarial Networks (GANs), FreeCodeCamp Forum, January 2018, Link

Adaptively Scaling Cosine Logits (AdaCos)[1]

- Adaptive Loss function – based on Cosine Similarity
- Predicted Probability => $P_{i,j} = \frac{e^{\tilde{s} \cdot cos\theta_{i,j}}}{\sum_{k=1}^{C} e^{\tilde{s} \cdot cos\theta_{i,k}}}$ where $\tilde{s}$ is Scaled hyperparameter
- Objective => Choose $\tilde{s}$ to $max \left\| \frac{\partial P_{i,y_i}(\theta)}{\partial \theta} \right\|$, thus $\tilde{s} \approx \sqrt{2} \cdot log(C-1)$



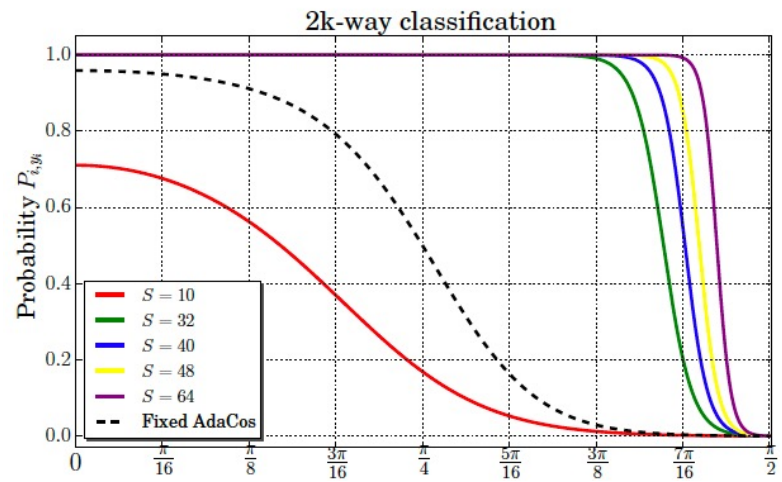


Figure 6: Cosine Loss and $P_{i,j}$ w.r.t. $\theta_{i,j}$

[1] Xiao Zhang, Rui Zhao, Yu Qiao, Xiaogang Wang, AdaCos: Adaptively Scaling Cosine Logits for Effectively Learning Deep Face Representations, May 2019

MVTech Dataset

- Dataset for Anomaly Detection with focus on Industrial Inspection [1]
- High Resolution Images with Multiple defects

Figure 6 a: MVTech Dataset, [a] Defect free images (Training dataset) [b] Images with Defects (Test dataset) [c] Ground Truth images

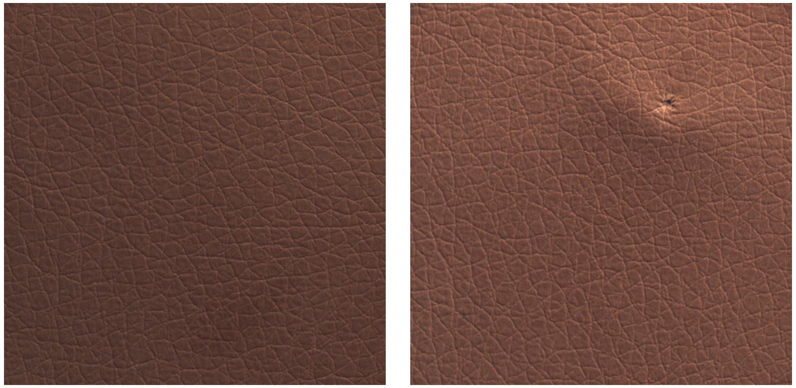


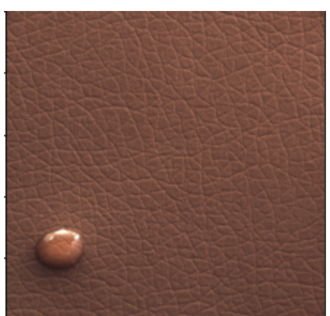
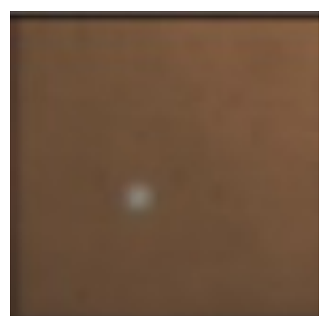
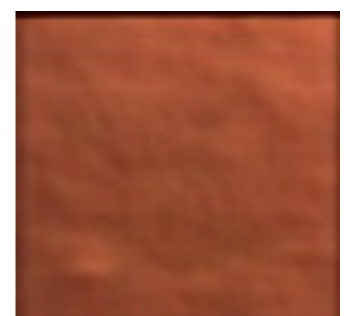
Figure 6 b: Leather Dataset, [Left Image] Defect free images (Training dataset = 245 images) [Right Image] Poked Leather (Test dataset = 124 images)

[2] MVTech Dataset (https://www.mvtec.com/company/research/datasets/mvtec-ad)

Evaluation

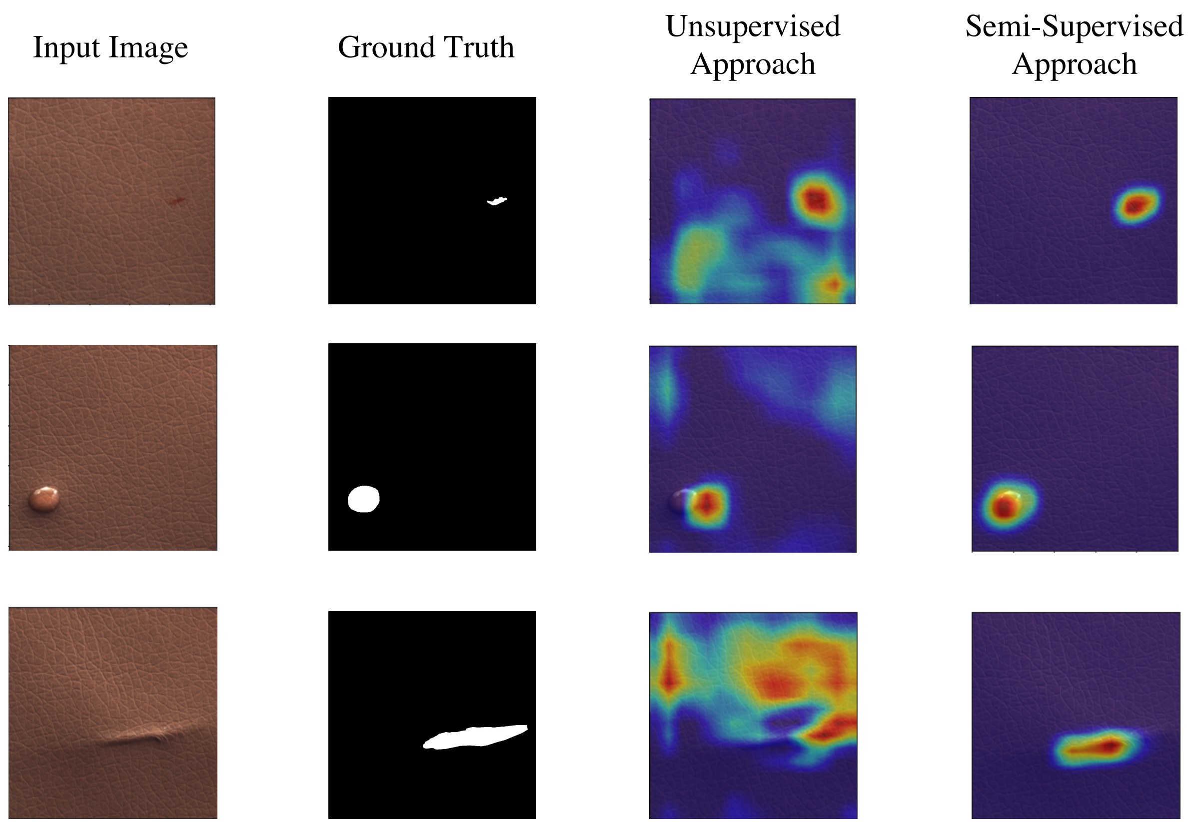
Subjective Evaluation

Reconstruction of Images

	Input Image	Unsupervised Approach	Semi-Supervised Approach
Defect Free Image			
Defective Image			

Saliency Map

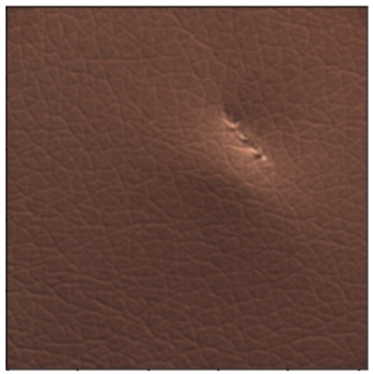
- Reconstruction of Images
- Dataset for Anomaly Detection with focus on Industrial Inspection [1]

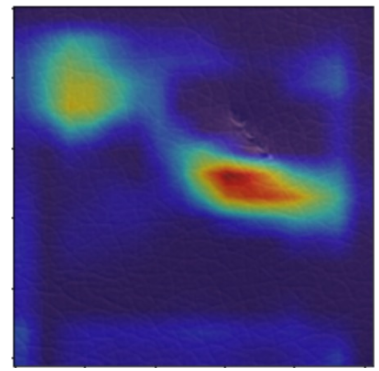


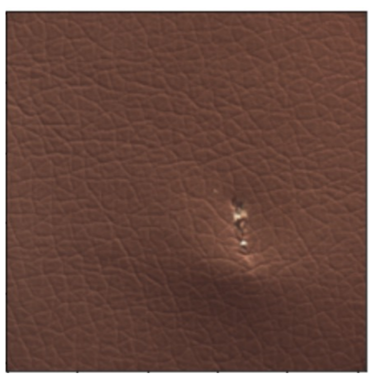
Saliency Map – Flawed

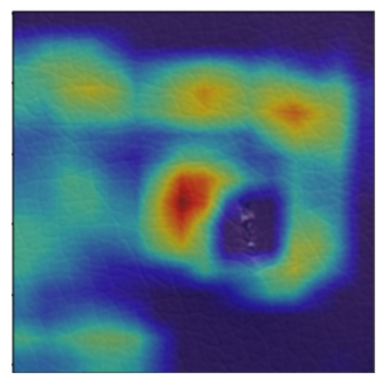
Input Image

Unsupervised
Approach









T-SNE

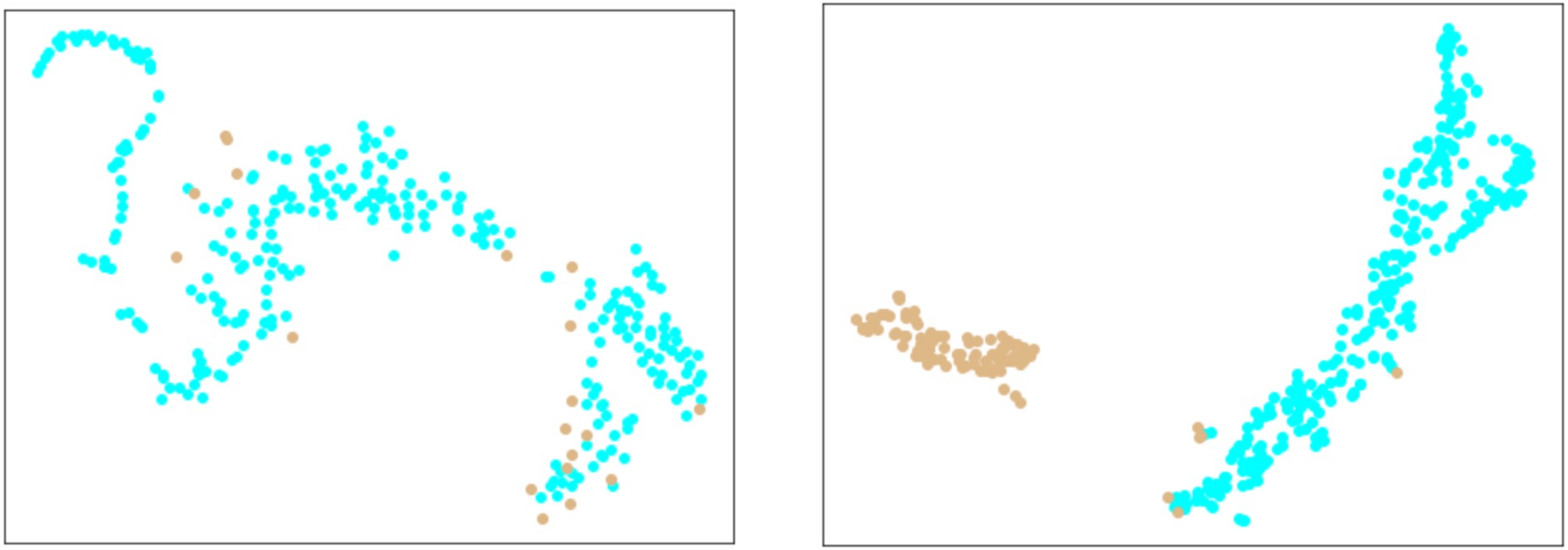
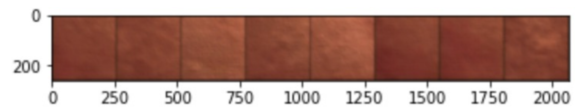


Figure 7: Unsupervised and Semi-Supervised Plot

Loss and IoU Curve




```
  0%|          | 0/10 [00:00<?, ?it/s]real_score: 0.8952 fake_score: 0.1767 Loss_D: 0.6088 errVAE: 0.128235
100%|██████████| 10/10 [00:03<00:00,  2.51it/s]
  0%|          | 0/37 [00:00<?, ?it/s]loss 0.7092 - acc@1 98.9796 - acc@5 100.0000 - val_loss 1.5378 - val_acc@1 82.6667 - val_acc@5 98.6667
Epoch [147/150]
100%|██████████| 37/37 [01:09<00:00,  1.88s/it]
100%|██████████| 10/10 [00:03<00:00,  2.55it/s]
  0%|          | 0/37 [00:00<?, ?it/s]loss 0.7191 - acc@1 98.2993 - acc@5 100.0000 - val_loss 1.4667 - val_acc@1 96.0000 - val_acc@5 100.0000
```

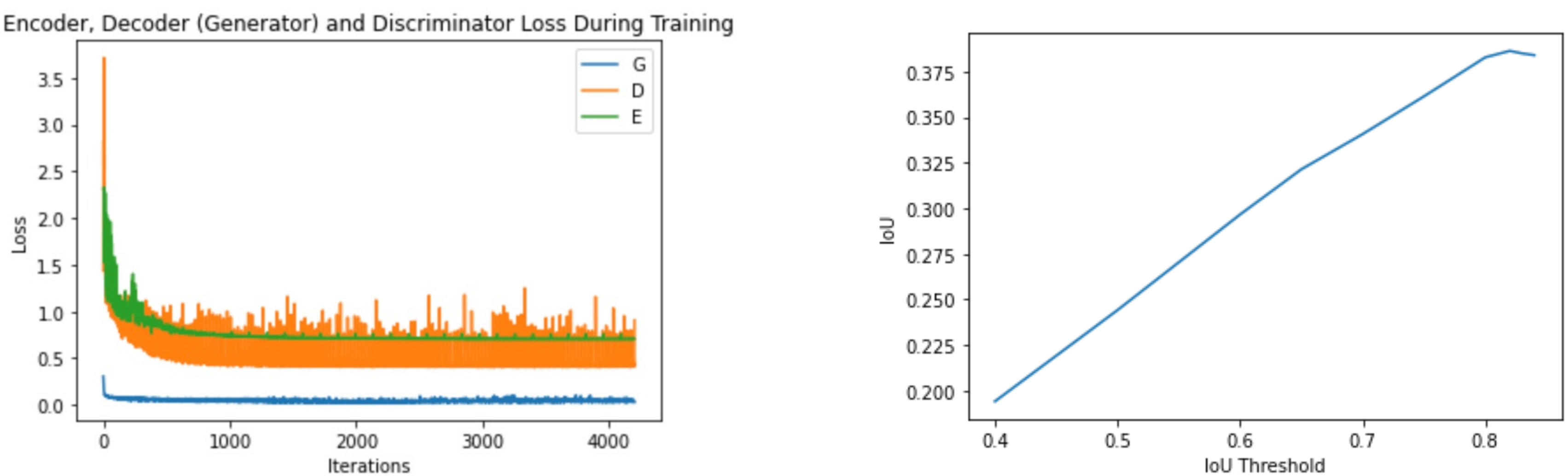


Figure 8: Validation Loss curve and IoU Curve for Unsupervised approach

Conclusion

- Implemented: VAE – GAN with Similarity loss
- To be Implemented:
  - Use of Convolutional Latent Variable
  - Implement Attention Mechanism
  - Test on other classes – screw, transistor etc.

Thank you