

Image Analysis & Computer Vision





Anomaly Detection Based on Autoencoder and Denoising Convolutional Neural Network

Project Presentation

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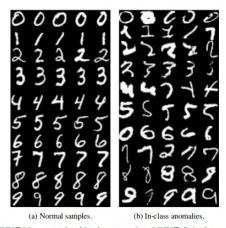
Presentation Outline

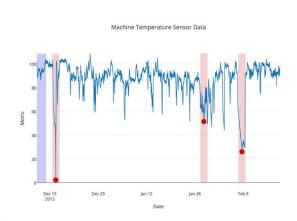
- Introduction
- Problem Definition
- Proposed Architecture
- Experiment Results
- Conclusion



What is Anomaly Detection?

- (Hawkins' Definition of Outlier, 1980) "An outlier (or anomaly) is an observation that differs so much from other observations as to arouse suspicion that it was generated by a different mechanism."
- "Finding patterns in given data that has new or unexplained characteristics."
- Depending on the context term may change: novelty, outlier, aberration, discordant observation etc.





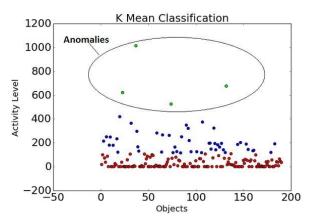
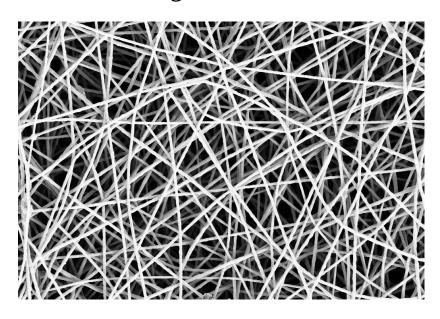


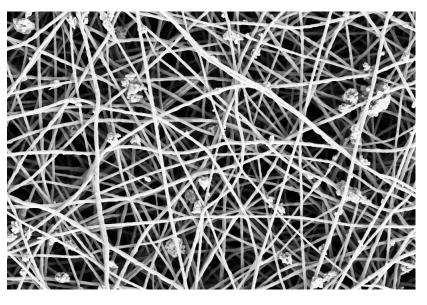
Figure 3: MNIST Most normal and in-class anomalous MNIST digits detected by RCAE.



Problem Definition

- We particularly examine automated detection of defects in nanofibrous materials
- Dataset is set of Scanning Electron Microscope (SEM) images
- Challenges
 - Filament pattern is geometrically pseudo random. (Does not align with a predefined texture)
 - Trade off between patch size, resolution and accuracy.
 - High variation in between images without defects.







Architecture Overview

- Architecture consists of an Autoencoder Network and a Denosining Network combined.
- Training of the architecture is sequential
- Considering:

$$\hat{x} = x + \epsilon : x \sim X \in \mathbb{R}^d, \quad \epsilon \sim \mathcal{N}(\mu, \sigma^2)$$

First the Autoencoder Network with the following objective function:

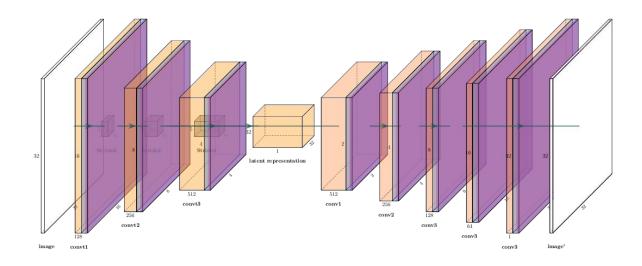
$$\mathcal{L}_{DAE} = \|x - (\psi \circ \phi)(\hat{x})\|^2$$

Then the Denoising Network is trained with fixed autoencoder network outputs with the following objective function:

$$\mathcal{L}_{Den} = \|x - \text{Den}((\psi \circ \phi)(x))\|^2$$



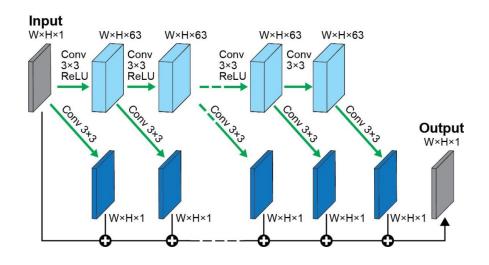
Autoencoder Network



- Encoder and Decoder Networks
- Encoder Network:
 - o 3 Layers of Convolution + Batch Normalization + Leaky ReLU with
 - \blacksquare Kernel size (5 x 5)
 - Stride (2 x 2)
 - Filters 128 > 256 > 512
 - Dense Layer with number of Nodes equal to the latent representation
- Decoder Network :
 - o 5 Layers of Transposed Convolution + Batch Normalization + Leaky ReLU with
 - \blacksquare Kernel size (5 x 5)
 - Stride (2 x 2)
 - Filters 512 > 256 > 128 > 64 > 1
- Trained with reconstruction error
- Anomaly score is defined with ℓ_2 norm of the reconstruction error



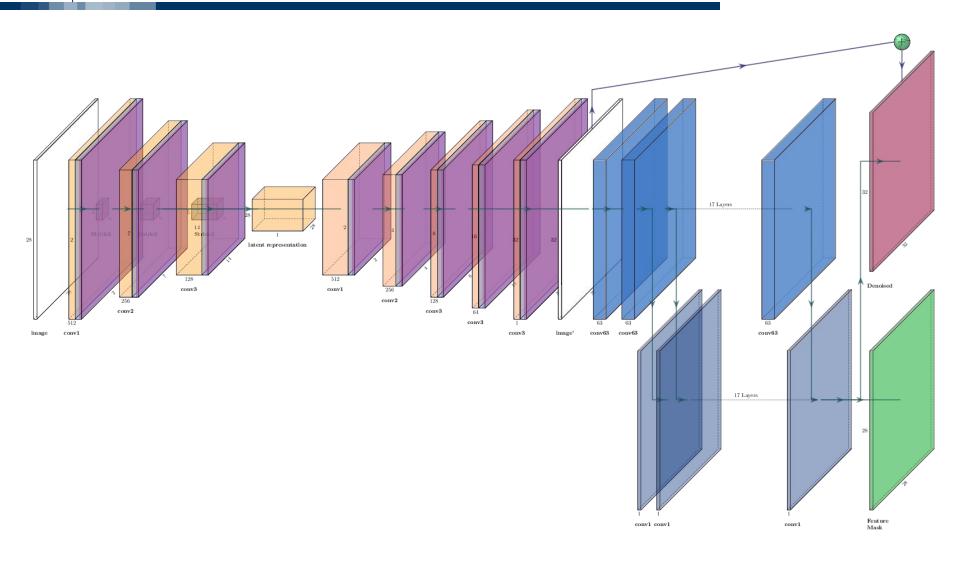
Denoising Network



- 20 fully convolutional layers of network with two branches:
 - 63 3x3 Conv filters trained
 - 1 3x3 Conv filter trained and accumulated through layers
- Trained by reconstruction error
- For anomaly score, residual computed with
 - Smooth Reconstruction or
 - Feature mask



Proposed Architecture





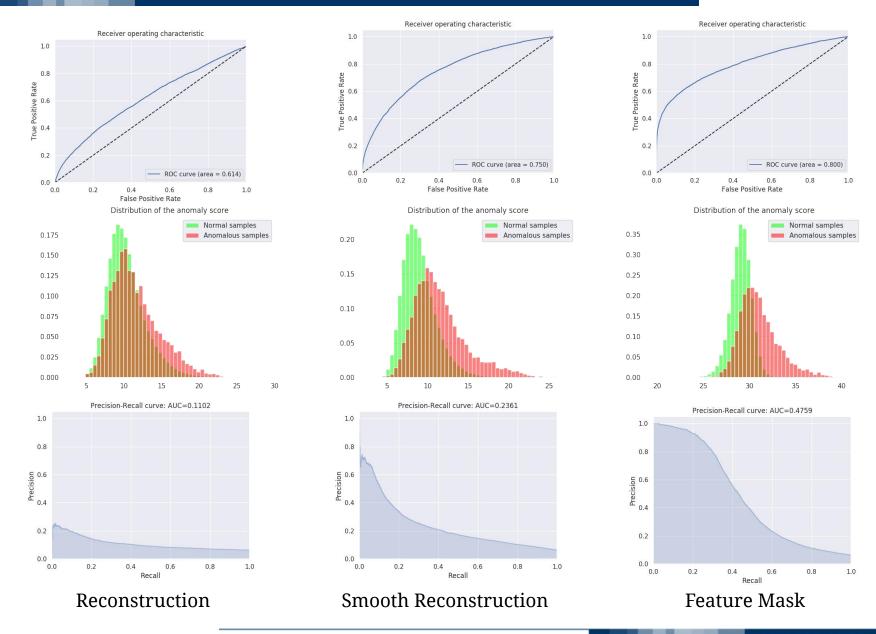
Experiment Results

	Performance Metrics			
Score Type	AUROC	Precision	Recall	F1 Score
Reconstuction	0.6135	0.12040	0.28527	0.16933
Smooth Reconstruction	0.75003	0.22560	0.35636	0.27629
Feature Mask	0.80022	0.60295	0.38098	0.46692

- Experiment results for Denoising Autoencoders are considered.
- Smoothing reconstruction improves the precision and recall capacity of the model.
- Computing residual with feature mask instead of the smooth reconstruction for anomaly score greatly increases precision while also improving the recall capacity.

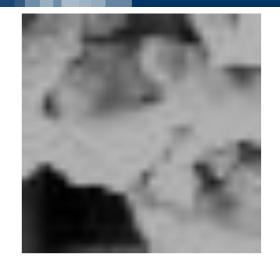


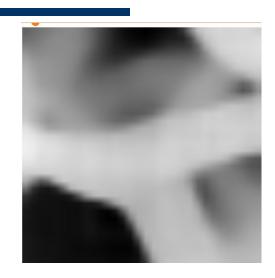
Experiment Results





Qualitative Results



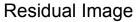


Query Sample

Reconstruction

Denoised Reconstruction







Feature Mask



Conclusion

- Automated Anomaly Detection is implemented with autoencoder and fully convolutional denoising network.
- Three different autoencoder methods are tested.
- Different outputs from denoising network explored for anomaly score.

Future works are possible with extension on Generative Adversarial Networks and further examinations of FC denoising network.



Thank you for your attention