Anomaly Detection & Localization using

Autoencoder

**Dataset:** MVTec Anomaly Detection Dataset

**Objective:** Identify and localize defects using unsupervised deep learning.

**MVTec-AD Dataset (Cable Category)**

* - Real-world industrial images with and without defects.
* - Training: only 'good' images (normal, defect-free).
* - Testing: includes both 'good' and defective images.
* - Each defective test image has a pixel-level ground truth mask.
* - Example defects: missing wires, cable damage, twisted end

**Model Architecture – Convolutional Autoencoder**

* **Encoder:**
* Conv2d(3→64), ReLU
* Conv2d(64→128), ReLU
* Conv2d(128→256), ReLU
* **Decoder:**
* ConvTranspose2d(256→128), ReLU
* ConvTranspose2d(128→64), ReLU
* ConvTranspose2d(64→3),Sigmoid

The model is trained to reconstruct normal images using MSE loss.

**Anomaly Detection Pipeline**

1. Train autoencoder on normal images only.

2. During testing, reconstruct both normal and anomalous images.

3. Compute reconstruction error per pixel: MSE across RGB channels.

4. Apply Gaussian smoothing (σ=2) to the error map.

5. Apply Otsu thresholding to obtain a binary anomaly mask.

6. Use morphological operations to refine the mask.

**Evaluation Metrics**

**Pixel-level AUROC:**

* Measures overlap between predicted anomaly heatmap and ground truth mask.
* High value = accurate localization.

**Image-level AUROC:**

* Measures binary classification: is image normal or anomalous?
* Uses max pixel error as image-level anomaly score.

**Qualitative Results – Output Visualization**

Each test result visualized as 4 panels:

1. Real Image – input image from test set.

2. Heatmap – per-pixel reconstruction error (hot = high error).

3. Filtered Binary Mask – predicted anomaly region after thresholding.

4. Ground Truth – actual defect area (white pixels).

Helps evaluate both detection and localization performance.

**Observations & Performance**

* Autoencoder detects major and obvious defects effectively.
* Struggles with subtle, low-contrast, or tiny defects.
* False positives can occur in textured or cluttered backgrounds.

Pixel-level AUROC ≈ High (good localization);

Image-level AUROC ≈ High (good classification).

**Limitations & Challenges**

* No explicit localization supervision during training.
* Autoencoder may memorize background textures.
* Heatmap thresholding (Otsu) is data-dependent.
* High-resolution defects may be downsampled/lost.
* Cannot distinguish between structural vs harmless variations.

**Future Enhancements**

* Replace MSE loss with SSIM or perceptual loss (preserve structure).
* Add skip connections (UNet-style autoencoder).
* Use PatchCore, FastFlow, or DRAEM for better detection accuracy.
* Integrate multi-scale features or attention mechanisms.
* Add quantitative results comparison with other models.

**Conclusion**

* A simple convolutional autoencoder can detect and localize industrial defects.
* Works well for many visible anomalies, but needs improvements for precision.
* Serves as a strong baseline for unsupervised anomaly detection.
* Easy to deploy and interpret with reconstruction-based methods.