A Critical Evaluation of Diffusion Models: Exploring Their Limits in Open-World Anomaly Detection

Saksham Madan (Roll no. 24124040)
Kushal Shrivastava (Roll no. 24124025)
Arnav Raghuvanshi (Roll no. 24124007)

Department of Mathematical Science
Indian Institute of Technology (BHU), Varanasi

Supervisor: Dr. Santwana Mukhopadhyay

Outline

Motivation

- Industrial inspection often deals with:
  - tiny scratches, small holes, colour shifts, loose threads, etc.
  - These are *local, high-frequency* defects on otherwise regular textures.
- Classical idea:
  - Learn what "normal" looks like,
  - Flag anything that deviates as an anomaly.
- Recent progress:
  - **Diffusion models** can generate extremely realistic images.
  - **CLIP** can compare images in a semantic feature space.
- Natural question:

Can we use these modern generative models to reconstruct a *clean* version of an image and detect anomalies from the differences?

Reconstruction-Based Anomaly Detection

- Setup:
  1. Train a model only on **normal** images.
  2. Given a test image x, (maybe defective), ask the model for a reconstruction $\hat{x}$.
  3. Compare x and $\hat{x}$:
     - Large local differences $\Rightarrow$ likely anomaly.
- Intuition:
  - The model learns the manifold of normal images.
  - Test images are projected back onto this manifold.
  - Anomalies are "pushed away" from the manifold and show up in the residual $x - \hat{x}$.
- Works relatively well with:
  - autoencoders, some GAN-based models.
- Our work: does this paradigm make sense with **latent diffusion** + **CLIP**?

Goals of This Project

- **Main goal:** critically evaluate latent diffusion models for open-world industrial anomaly detection.
- Sub-goals:
  - Test three practical pipelines built around Stable Diffusion:
    1. Small UNet on top of SD latents,
    2. SD `img2img` with prompts,
    3. LoRA fine-tuning on normal textures.
  - Combine pixel-based and CLIP-based scores into a hybrid anomaly score.
  - Analyse not just the numbers, but also:
    - reconstruction behaviour,
    - hyperparameter sensitivity,
    - and *why* the model behaves as it does.

Dataset: MVTec AD

- **MVTec Anomaly Detection** is a standard benchmark:
  - 15 categories: e.g. carpet, tile, wood, bottle, metal nut, etc.
  - Each category has:
    - many normal training images,
    - test images with annotated defects.
- Properties:
  - Defects are often small, local, and embedded in repetitive textures.
  - Good stress test for any reconstruction model:
    - It must preserve fine details,
    - but selectively remove irregularities.

MVTec AD Example (Carpet Category)

Good | Color defect | Hole | Metal piece | Extra thread

These defects are small, local perturbations on a largely repetitive background.

Research Design

- **Type:** comparative exploratory study.
- High-level plan:
  1. Implement multiple reconstruction pipelines using latent diffusion.
  2. For each pipeline:
     - generate reconstructions on MVTec test images,
     - compute anomaly scores (pixel + CLIP),
     - visualize heatmaps showing where the model "thinks" anomalies are.
  3. Compare with a CLIP feature-based baseline.
  4. Use mathematical and architectural reasoning to interpret:
     - why certain defects are missed,
     - why textures drift.

Implementation Details

- **Software**
  - Python, PyTorch.
  - HuggingFace Diffusers (Stable Diffusion, DDIM scheduler).
  - OpenAI CLIP.
- **Compute**
  - Kaggle GPU environment (limited VRAM).
  - Required optimizations:
    - attention-slicing,
    - half-precision (fp16),
    - small batch sizes.
- **Models**
  - Stable Diffusion v1.5,
  - CLIP ViT-B/32 as image encoder.

Diffusion Models

- Forward process (noising):
  - Start from a clean sample x_0,
  - Iteratively add Gaussian noise:

$$x_t = \sqrt{\bar{\alpha}_t}\, x_0 + \sqrt{1 - \bar{\alpha}_t}\, \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, I).$$

  - For large t, x_t becomes nearly pure noise.
- Reverse process (denoising):
  - A neural network is trained to *predict the noise* at each step.
  - Informally: "Given a slightly noisy image, what clean image could have produced it?"
  - Sampling: start from noise, run the learned reverse steps to get a new image.
- Important: this reverse process is **generative**, not an exact inverse map.

Latent Diffusion (Stable Diffusion) – Details

- Directly applying diffusion in pixel space is expensive.
- Latent diffusion uses a VAE:
  - Encoder: $\mathrm{Enc}(x) = z$ (compressed latent representation).
  - Decoder: $\mathrm{Dec}(z) \approx x$.
- Diffusion runs on z instead of x:
  - Much smaller dimensionality,
  - Faster and cheaper.
- But:
  - The VAE encoding is *lossy*.
  - High-frequency details (tiny scratches, small holes) are partially discarded.
  - This is the **information bottleneck** of latent diffusion.

CLIP – A Semantic Distance Between Images

- CLIP has:
  - an image encoder $f(x)$,
  - a text encoder $g(t)$,
  - both map into a shared feature space.
- Training idea:
  - Pairs (x_i, t_i) that belong together should have high similarity,
  - Mismatched pairs should have low similarity.
- In our use:
  - We focus on $f(x)$, the image embeddings.
  - Given input x and reconstruction $\hat{x}$:

$$\text{CLIP distance} = 1 - \frac{\langle f(x), f(\hat{x}) \rangle}{\|f(x)\| \, \|f(\hat{x})\|}.$$

  - If CLIP believes they are semantically different, this distance is large.

LoRA – Parameter-Efficient Fine-Tuning

- Full fine-tuning of a diffusion model is expensive (millions of parameters).
- LoRA modifies each weight matrix W_0 by a low-rank correction:

$$W = W_0 + BA, \quad B \in \mathbb{R}^{d \times r},\ A \in \mathbb{R}^{r \times k},\ r \ll \min(d, k).$$

- Interpretation:
  - W_0 encodes general knowledge,
  - BA encodes a small adaptation to a new domain (here: clean industrial textures).
- For us:
  - LoRA is applied to the diffusion UNet,
  - The VAE encoder/decoder remain unchanged,
  - So the fundamental compression bottleneck still exists.

Three Reconstruction Pipelines

- **1. Small UNet on SD Latents**
  - Take $z = \mathrm{Enc}(x)$ from Stable Diffusion.
  - Add a smaller UNet that tries to "repair" z before decoding.
  - Hope: recover some of the lost fine texture.
- **2. Stable Diffusion `img2img`**
  - Start from the encoded version of x,
  - Add noise controlled by a parameter called *strength*,
  - Run the diffusion process with a prompt like "a flawless carpet",
  - Try to keep the structure while removing defects.
- **3. LoRA Fine-Tuning**
  - Train a small LoRA module on normal images,
  - Encourage the model to generate the typical clean texture of each category.

Hybrid Anomaly Scoring

- Given input x and reconstruction $\hat{x}$, we compute:
  - Pixel error: $\mathrm{MSE}(x, \hat{x})$,
  - CLIP distance: $1 - \cos(f(x), f(\hat{x}))$.
- Hybrid score:

$$S_{\text{hybrid}}(x) = \alpha \cdot \mathrm{MSE}(x, \hat{x}) + (1 - \alpha) \cdot (1 - \cos(f(x), f(\hat{x}))),$$

  with $\alpha \in [0, 1]$.
- Interpretation:
  - Pixel term: sensitive to small local changes.
  - CLIP term: sensitive to semantic/texture-level changes.
  - Tuning α changes how "strict" we are about pixel vs semantic alignment.

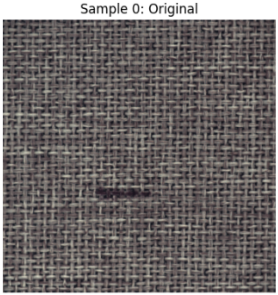
Hyperparameters and Metrics

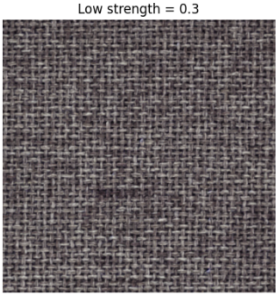
- **Diffusion Hyperparameters**
  - Strength: 0.1–0.7 (amount of noise added in `img2img`).
  - Guidance scale: 3.5–9 (how strongly we enforce the text prompt).
  - Steps: 20–50 (number of denoising steps).
- **Scoring Hyperparameters**
  - α: 0.3–0.9 (balance between pixel and CLIP contributions).
- **Evaluation Metrics**
  - AUROC (normal vs anomalous),
  - MSE, SSIM (reconstruction quality),
  - CLIP cosine similarity,
  - Qualitative heatmaps of $|x - \hat{x}|$.

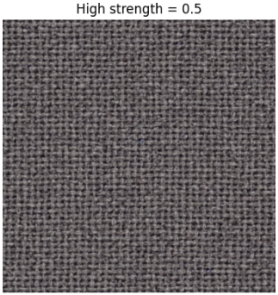
Summary of Experimental Findings

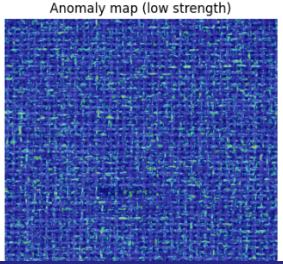
- **Small UNet on SD Latents**
  - Reconstructions remained blurry,
  - High-frequency textures lost in the VAE encoding were not recovered.
- **Stable Diffusion `img2img`**
  - Low strength:
    - The reconstruction is almost identical to the input,
    - Defects remain.
  - High strength:
    - Defects vanish,
    - But textures and sometimes shapes change significantly.
- **LoRA Fine-Tuning**
  - Some defects are softened or removed,
  - But we see colour shifts and style changes (identity drift).

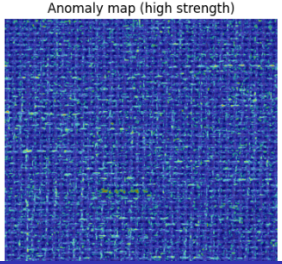
Effect of Diffusion Strength











Quantitative Metrics and Their Limitations

- AUROC values sometimes looked “acceptable”.
- However, deeper inspection showed:
  - Good AUROC sometimes came from global style changes,
  - Not from precise removal of defects on an otherwise unchanged background.
- In other words:

The model was often correct for the wrong reasons: it changed the whole texture, which correlated with anomalies, but did not give faithful reconstructions.

Information Bottleneck in the VAE

- Stable Diffusion uses $x \mapsto z = \mathrm{Enc}(x)$, z is much smaller than x.
- Approximate decoding: $x \approx \mathrm{Dec}(z)$.
- The reconstruction error $x - \mathrm{Dec}(\mathrm{Enc}(x))$ is not negligible:
  - It contains high-frequency texture details,
  - Exactly the information that distinguishes small defects from normal patterns.
- If an anomaly is smaller than this "VAE noise floor":

It gets washed out before the diffusion process even starts.

Small Defects vs Model Variance

- Suppose $x_{\text{anom}} = x_{\text{norm}} + \delta$, with δ a tiny defect.
- The model's own reconstruction noise and randomness is larger than δ:

$$\|x_{\text{anom}} - \hat{x}\| \approx \text{model drift} \gg \|\delta\|.$$

- Then:
  - The residual $x - \hat{x}$ is dominated by generative drift,
  - Not by the anomaly.
- This makes it hard to interpret high residuals as "true anomalies".

Generative vs Invertible

- The reverse diffusion is trained to approximate:

$$p_\theta(x_0 \mid x_T = \text{noise}),$$

  i.e. the distribution of plausible clean images.
- It is *not* trained to invert a specific x.
- In practice:
  - Small changes in random seed or guidance lead to noticeably different images.
  - So the map $x \mapsto \hat{x}$ is not a stable, near-identity map.
- For anomaly detection we would like:
  - $\hat{x}$ to be exactly x minus the defect,
  - but diffusion gives us "another clean example from the same class".

Contrast With Autoencoders

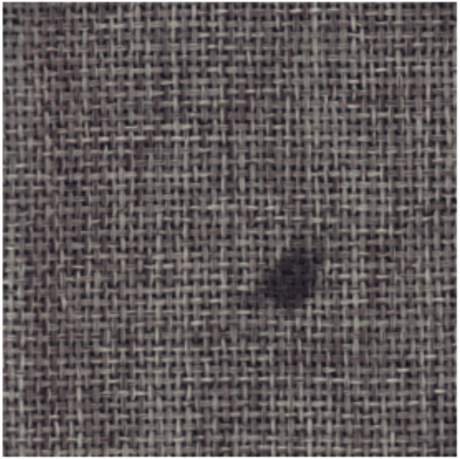
- Autoencoders are trained with an objective of the form:

$$\min \|x - \mathrm{AE}(x)\|^2,$$

  which explicitly encourages identity-preserving reconstruction.
- Diffusion models minimize a denoising loss, not a direct reconstruction loss in pixel space.
- As a result:
  - Autoencoders are biased toward copying the input (on normal data),
  - Diffusion models are biased toward sampling from the learned distribution.
- For reconstruction-based anomaly detection, this mismatch is fundamental rather than just an implementation detail.

Identity Drift – Visual Example

Original



Reconstruction

Output looks plausible and defect-free, but the exact texture and structure have changed: the identity of

Practical Challenges

- **Compute constraints**
  - Kaggle GPUs with limited VRAM,
  - Out-of-memory issues for large models and high resolution.
- **Approximate inversion**
  - Methods like DDIM inversion approximate the latent corresponding to x,
  - Not a mathematically exact inverse map, which adds additional drift.
- These limitations influenced:
  - how many experiments we could run,
  - and how thoroughly we could sweep hyperparameters.

Conclusion

Main Conclusion

Latent diffusion models (Stable Diffusion family) are **not well-suited** for reconstruction-based industrial anomaly detection that requires identity-preserving, pixel-accurate results.

- VAE compression removes the very fine-scale information we care about.
- The diffusion reverse process is generative, not a stable inverse of x.
- LoRA and CLIP improve scoring and texture adaptation, but do not remove the fundamental bottlenecks.
- Numeric metrics alone (like AUROC) can be misleading if we ignore these structural limitations.

Future Work

- Implement and compare with stronger baselines:
  - PatchCore, WinCLIP, and related methods.
- Explore pixel-space diffusion with more reconstruction-oriented objectives.
- Combine CLIP features with discriminative models:
  - e.g. training a classifier or segmenter on CLIP embeddings.
- Investigate invertible architectures:
  - Normalizing flows specifically tailored to industrial textures.

Project Artifacts

- Full written report.
- This slide deck summarizing the project.
- Experiment code and Kaggle scripts.
- Public repository:
  - `github.com/s4kr3d-w0r1d/exploratory_project`

The End

Thank You!