Visualizing the Impact of Data Perturbation on Image Models using Explainable AI

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UCDAVIS COMPUTER SCIENCE

VISUALIZATION & INTERFACE DESIGN INNOVATION

Motivation

Generative Image Models Are Trained on Scraped Art at Planetary Scale

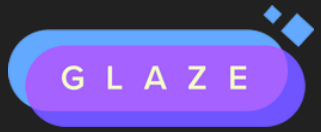
- Text-to-image systems (Stable Diffusion, DALL•E, Midjourney) rely on massive, scraped image–text compilations
- Training data overwhelmingly collected without artist consent or compensation
- Models can learn an artist's style from as few as a handful of examples

This Creates a New Technical Vulnerability:

- Artists are now exposed to:
  - Style Mimicry
  - Signature Reproduction
  - Dataset Contamination

- Training pipelines assume benign data
- That assumption is now false

Two Fundamentally Different Production Philosophies



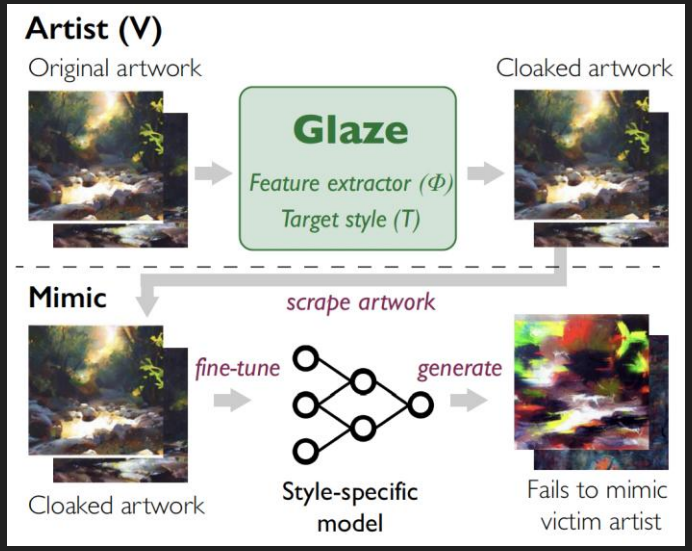
Defensive Style Cloaking Shan et al. (2023)

- Perturbs artwork toward a **surrogate style**
- Preserves content but **disrupts style learning**
- Acts in feature space, not pixel space
- **Goal**: Prevent style mimicry

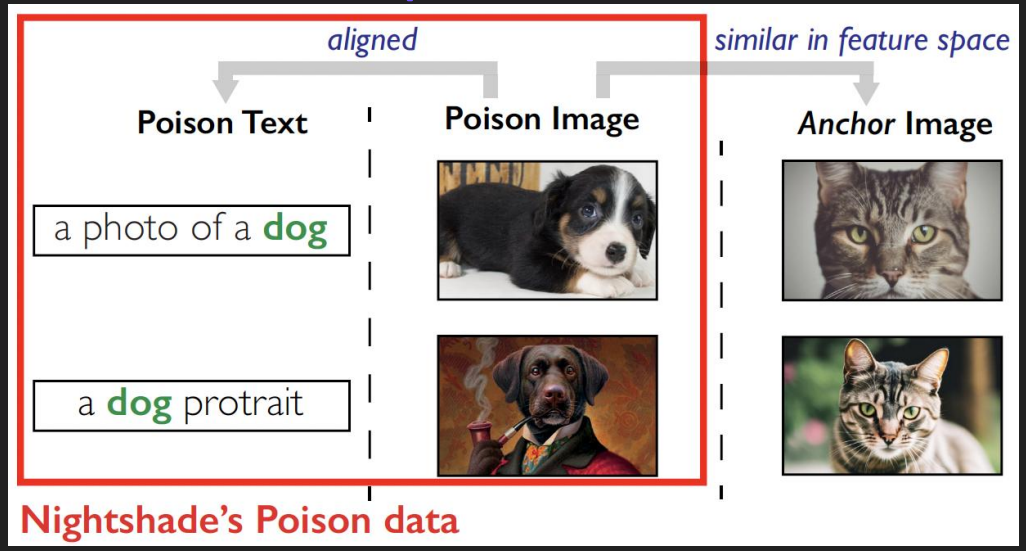
Offensive Concept Corruption Shan et al. (2024)

- Prompt-specific poisoning
- Misaligns visual features and semantic labels
- Corrupts the model's internal concept representation
- Goal: Destroy class-level understanding

Mechanistic Formation of Feature-Space Poisons



Shan et al. (2023)

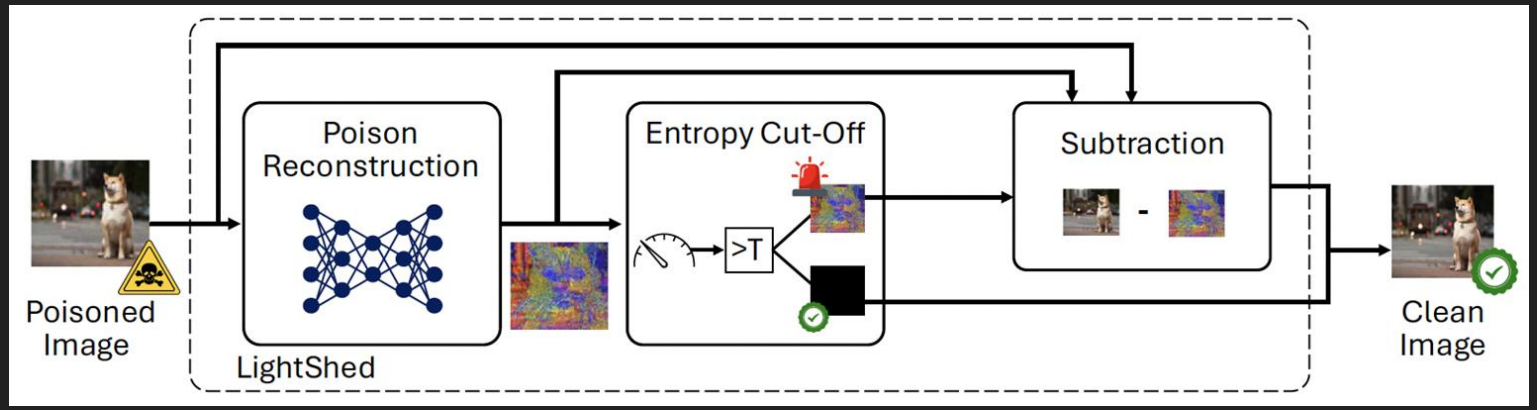


Shan et al. (2024)

- Both methods operate in feature space, not pixel space
- Glaze maximizes feature-space displacement toward surrogate styles
- Nightshade enforces cross-modal misalignment during training
- These mechanisms inject structured, low-entropy perturbations
- Distinct objectives imply distinct internal & spectral signatures

The Adversarial Arms Race: Purification Emerges

- Protection methods rapidly triggered **automated purification**
- Early countermeasures: **noisy upscaling, filtering, reconstruction**
- **LightShed**: autoencoder for detection, reconstruction, and removal
- Detection based on **entropy of reconstructed perturbation**
- Establishes purification as the current state of the art

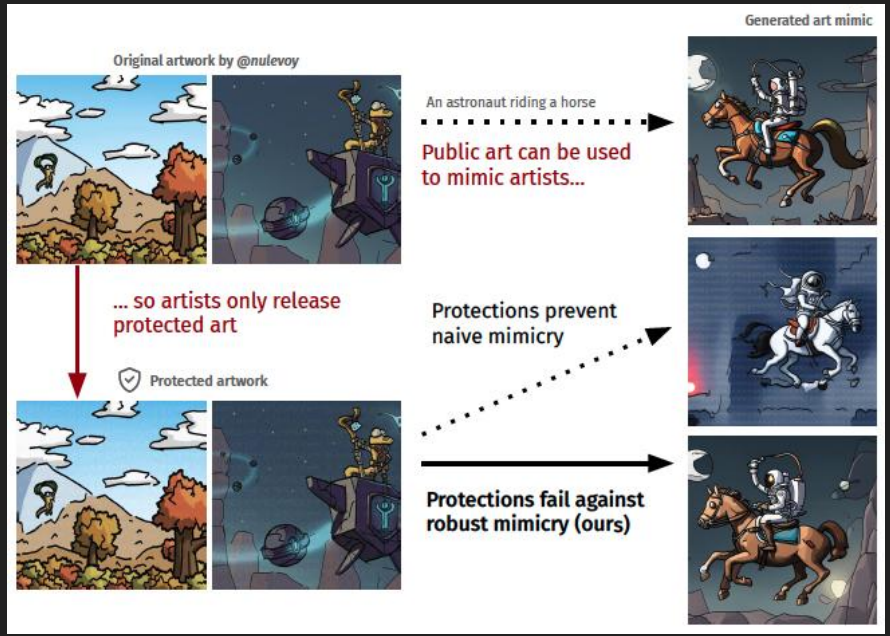


Foerster et al. (2025)

Limits of Current Protection and Purification

- Public art enables **robust style mimicry**
- Protections prevent **naïve imitation**
- Protections fail under **robust training pipelines**

- Shows limits of **both poisoning and purification**
- Motivates need for **interpretability, not just detection**



Hönig et al. (2024)

⇒ Few interpretability/XAI studies on protection tools/workarounds

Research Gaps

Prior work evaluates **whether poisoning succeeds or purification removes it.**

Missing understanding of:

- How poisoned images are represented **inside** detection models
- What structured signal the perturbations **inject into** the image itself

No prior work unifies:

- White-box neuron and latent-space analysis
- Black-box spatial sensitivity
- Black-box frequency-domain characterization

Empirical behavior rather than grounded in interpretable explainability lens.

Research Questions

- RQ1: How are clean vs. poisoned images represented in latent space?
- RQ2: What internal features and neurons drive poison detection?
- RQ3: Which perturbation patterns can evade detection?

Addressed through white-box and black-box XAI signal analysis

Overall Analysis Pipeline

Clean images → poisoned with Glaze, Nightshade, Nightshade→Glaze

White-box branch (LightShed):

- Latent bottleneck embeddings (t-SNE)
- Layer-wise encoder activations
- Reconstruction entropy for detectability

Black-box branch (model-agnostic):

- Spatial sensitivity via occlusion maps
- Frequency structure via FFT and radial spectra

Integrates **inside-model** and **inside-signal** perspectives

Dataset and Poisoning Protocol

9 total images spanning distinct artistic styles

4 variants per image:

- Clean
- Glaze
- Nightshade
- Nightshade → Glaze

Default protection settings for realism and minimal visual distortion

All variants processed through a uniform analysis pipeline.

Latent Representation of Clean Vs. Poisoned Images

Encoder **bottleneck embeddings** extracted from LightShed

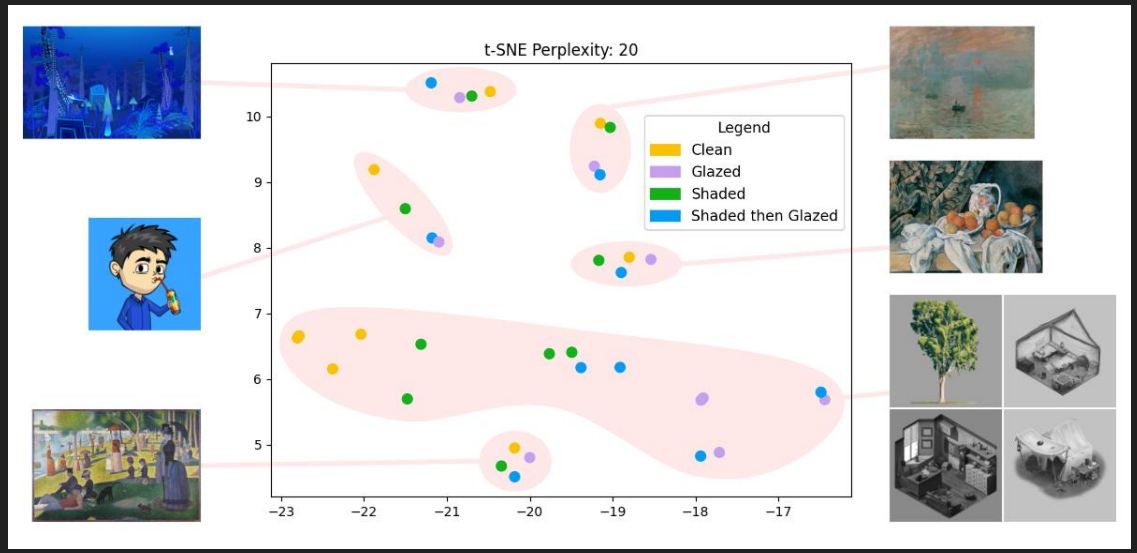
t-SNE used for 2D projection of latent space

Compares Clean, Glaze, Nightshade, Nightshade → Glaze

Tests whether poisoning creates **separable latent structure**

Latent Clustering in Bottleneck Space

- Clean images form tight clusters by artistic style
- Nightshade variants separate clearly from clean images
- Glaze variants form distinct subclusters within each style
- Nightshade → Glaze overlaps most closely with Glaze-only
- No consistent global shift vector across poisoning methods

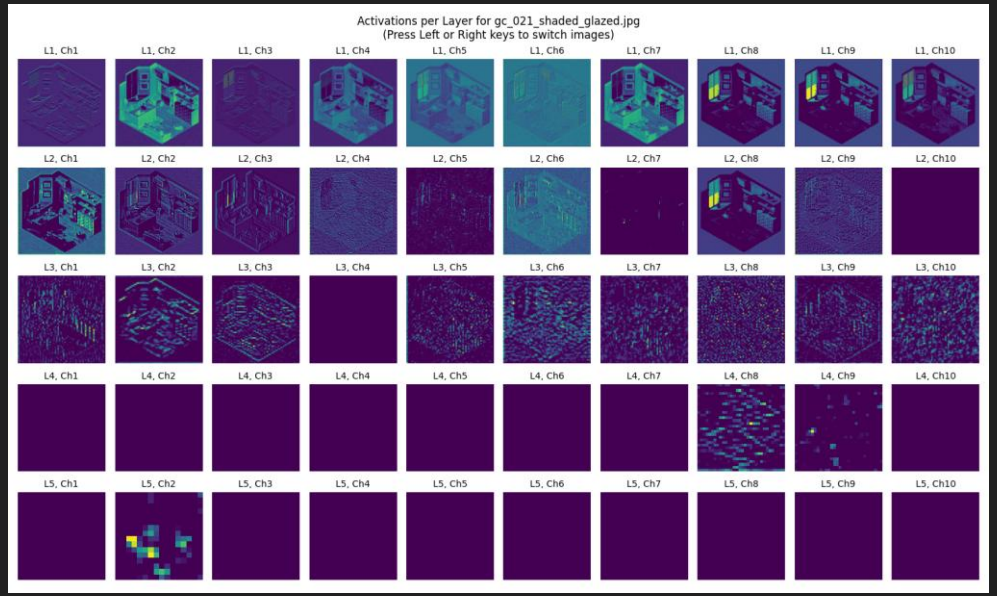


Feature Activation

- Analyze LightShed encoder convolutional layers
- Visualize channel-wise activation maps
- Track where perturbation responses first emerge
- Localize layers and neurons driving reconstruction
- Links internal activation patterns to detectability

Feature Activation

Identify layers/neurons responsible for poison reconstruction



Layer-Wise Activation Emergence

Layer 1 - minor differences

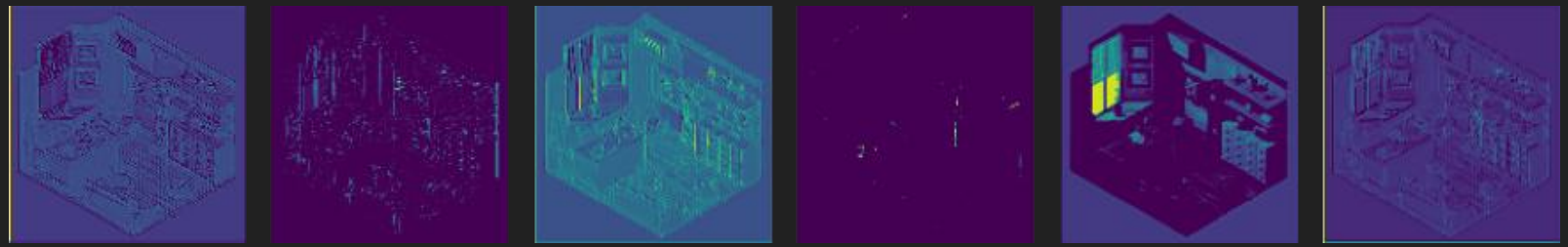
Clean

Shaded + Glazed

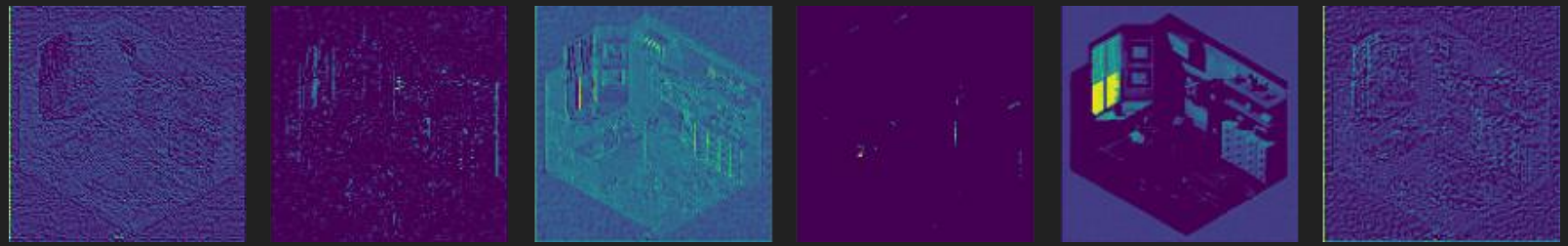
Layer-Wise Activation Emergence

Layer 2 - noticeable differences

Clean



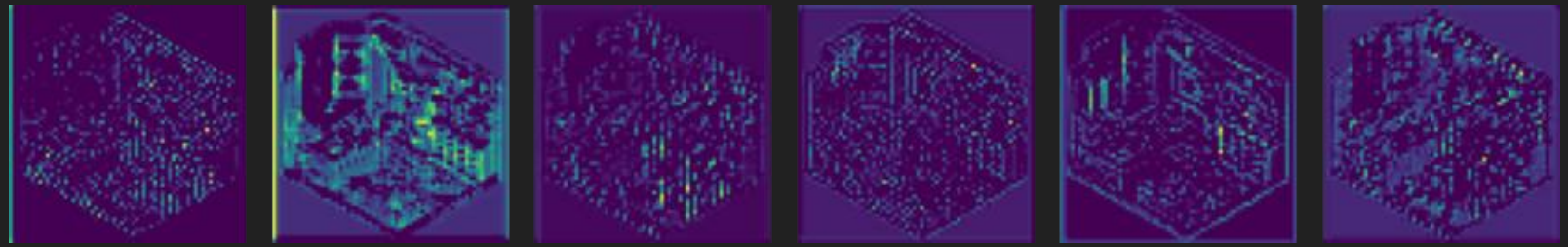
Shaded + Glazed



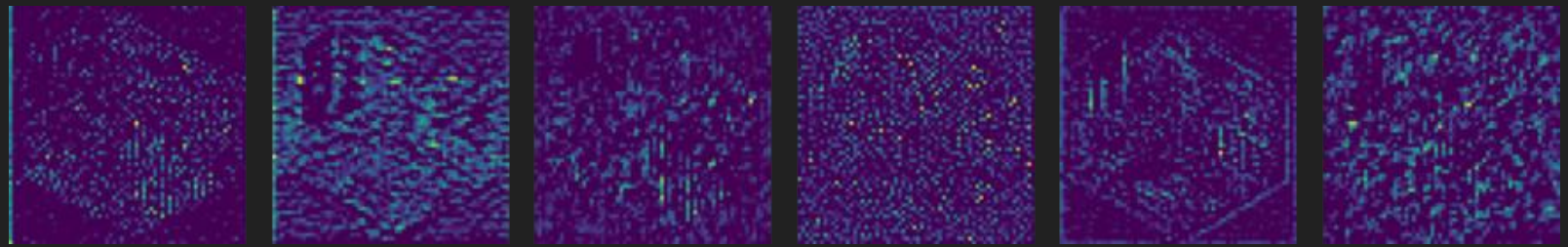
Layer-Wise Activation Emergence

Layer 3 - clear differences

Clean



Shaded + Glazed



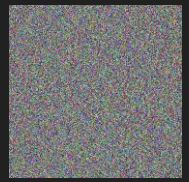
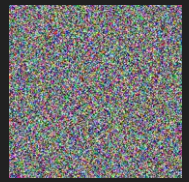
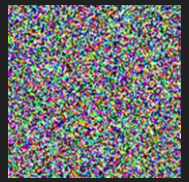
Detectability, Entropy & Evasion

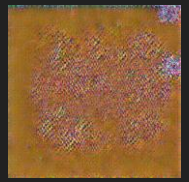
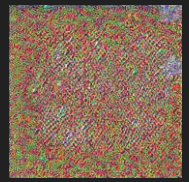
- Study when **perturbations trigger detection**
- LightShed detects based on **reconstruction entropy**
- Test synthetic noise and **procedural perturbations**
- Vary mask lightness and **spatial structure**
- Quantify **detectability vs. entropy relationship**

Experimental Design: Base, Noise & Masks

Base Image

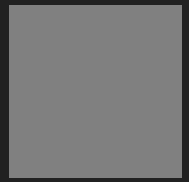
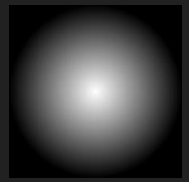
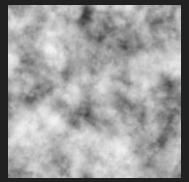
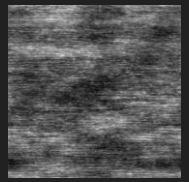
Noises

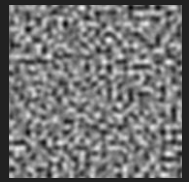




Gauss & Upscaled Gauss *Glaze & Nightshade Noise*

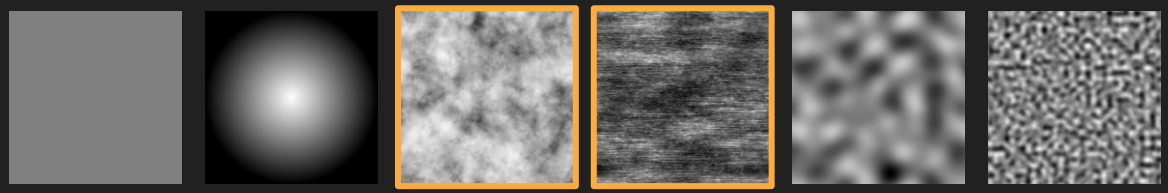
Procedurals



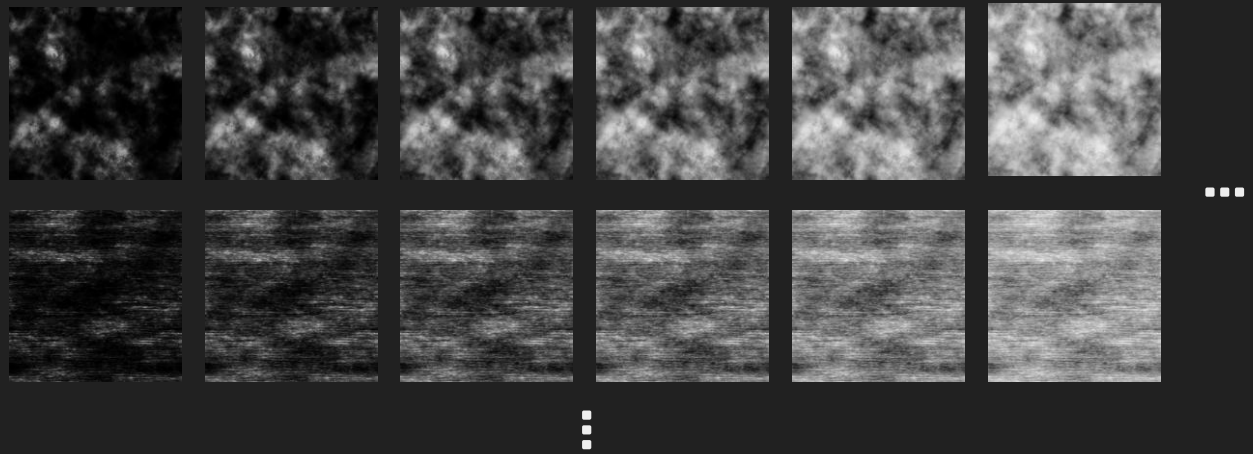
Reducing Detectability

Procedurals



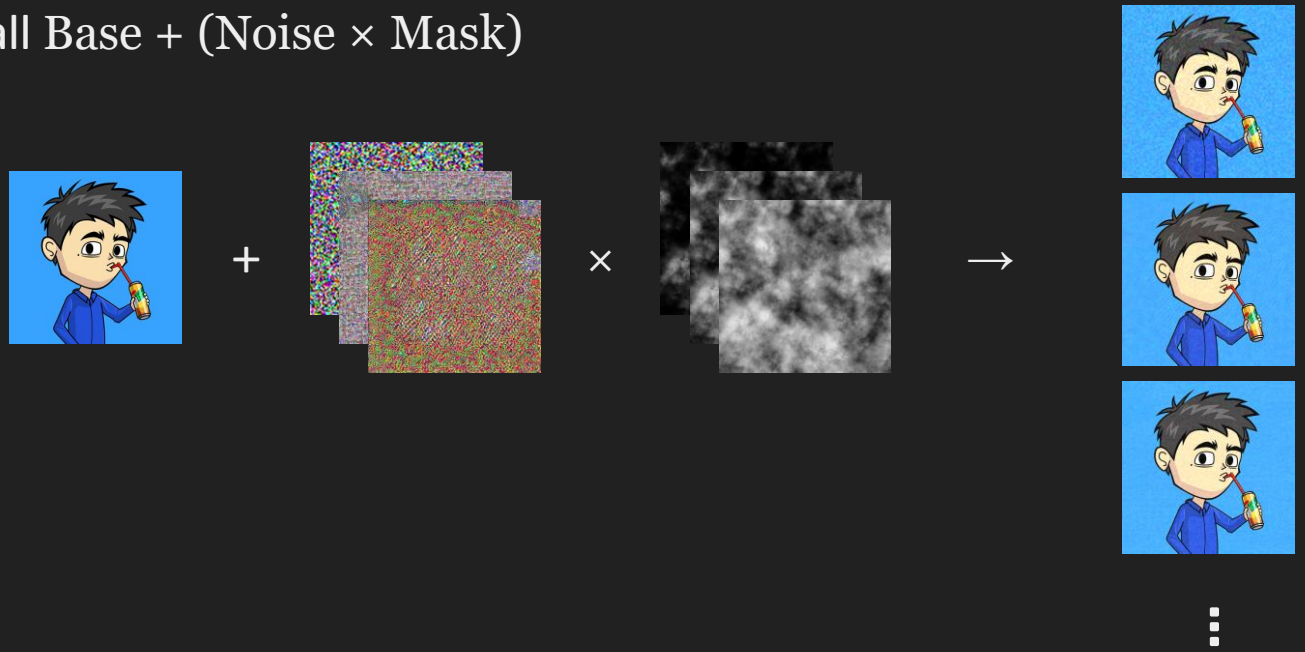
Lightness: *0.1* *0.2* *0.3* *0.4* *0.5* *0.6*

Masks



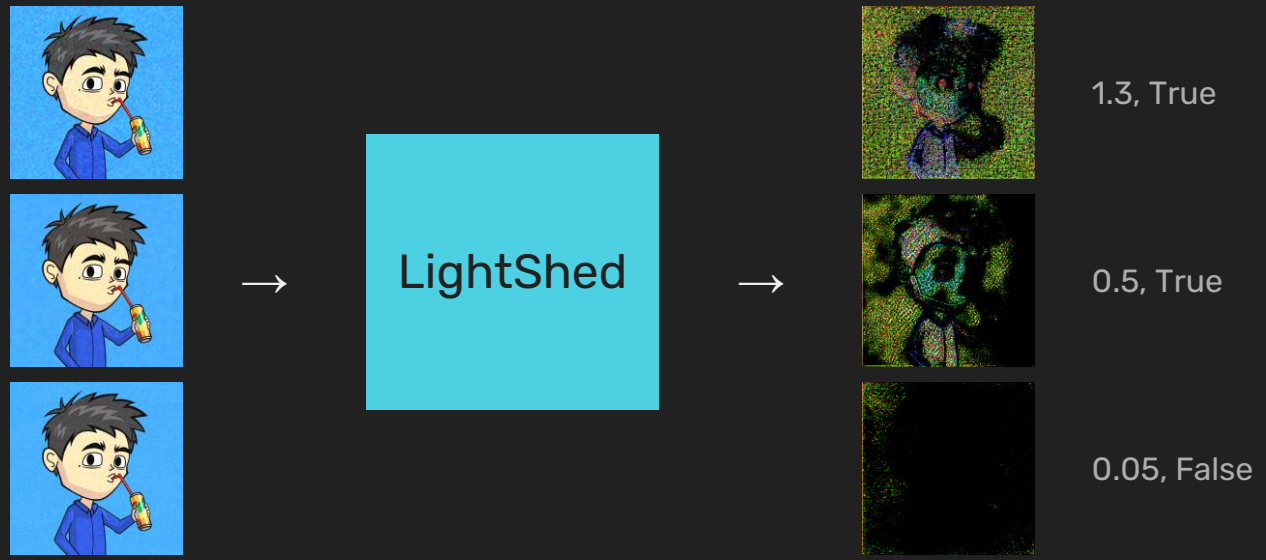
Reducing Detectability

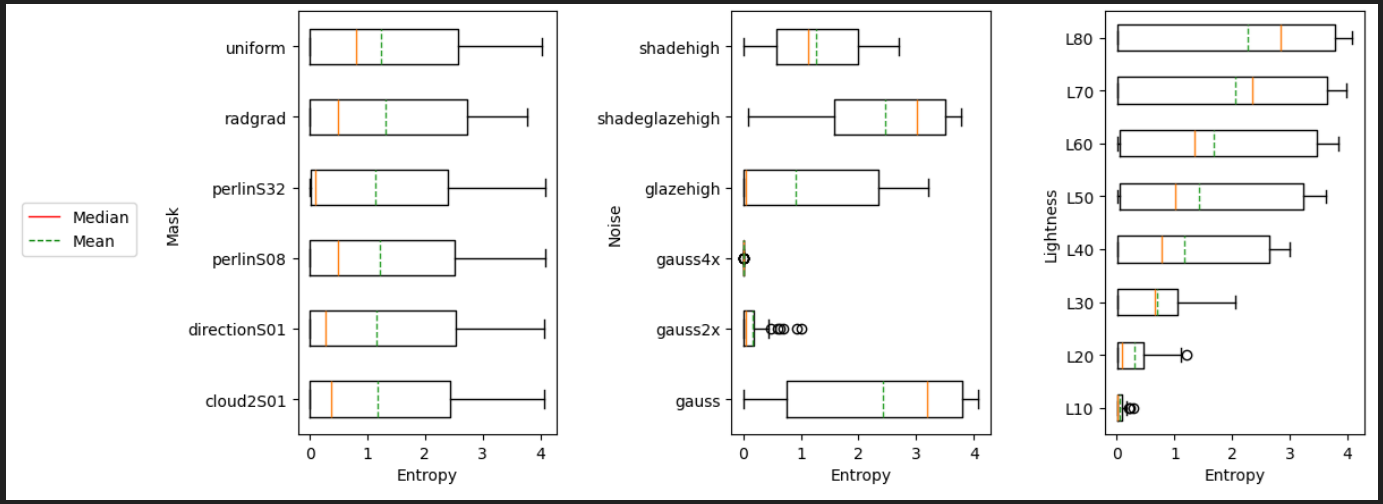
Permute all Base + (Noise × Mask)



Reducing Detectability

Process with LightShed
Return Entropy & Detected (> 0.07) for each image





Mask	Entropy	Detect	Noise	Entropy	Detect	$\mathcal{L}$	Entropy	Detect
Uniform	1.231	60.4%	Gauss	2.418	77.1%	0.1	**0.048**	**30.6%**
Radial Gradient	1.311	60.4%	Gauss-2x	0.164	41.7%	0.2	0.303	50.0%
Clouds2	1.177	64.6%	Gauss-4x	**0.002**	**0%**	0.3	0.700	61.1%
Directional	1.152	62.5%	Glazed	0.908	50.0%	0.4	1.166	63.9%
Hi-Freq Perlin	**1.143**	**52.1%**	Shaded	1.271	93.8%	0.5	1.416	72.2%
Low-Freq Perlin	1.208	62.5%	S+G	2.460	100%	0.6	1.688	72.2%
						0.7	2.049	66.7%
						0.8	2.261	66.7%

Detectability vs. Entropy

- Upscaled Gaussian noise shows lowest detection rate
- Glaze and Nightshade noise detected most reliably
- Detection peaks at mid-range mask lightness (~0.5–0.6)
- Very low and very high densities reduce detection reliability
- Confirms entropy alone is not sufficient for detectability

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Black-Box Analysis #1: Spatial & Frequency Structure

Analyze perturbations using input–output only methods

- No access to model internals

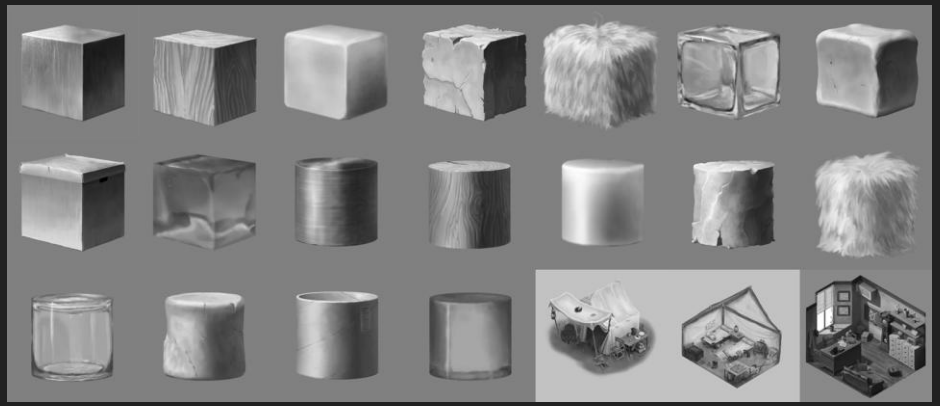
Two complementary views:

- Spatial sensitivity (**occlusion** analysis)
- Frequency structure (**FFT** and **radial profiles**)

Probes how the signal behaves, not how the model is built.

Black-Box Dataset & Occlusion Sensitivity Method

- 42 total images for black-box analysis
- 21 stylized 3D models with stylized shading
- 21 digital illustrations

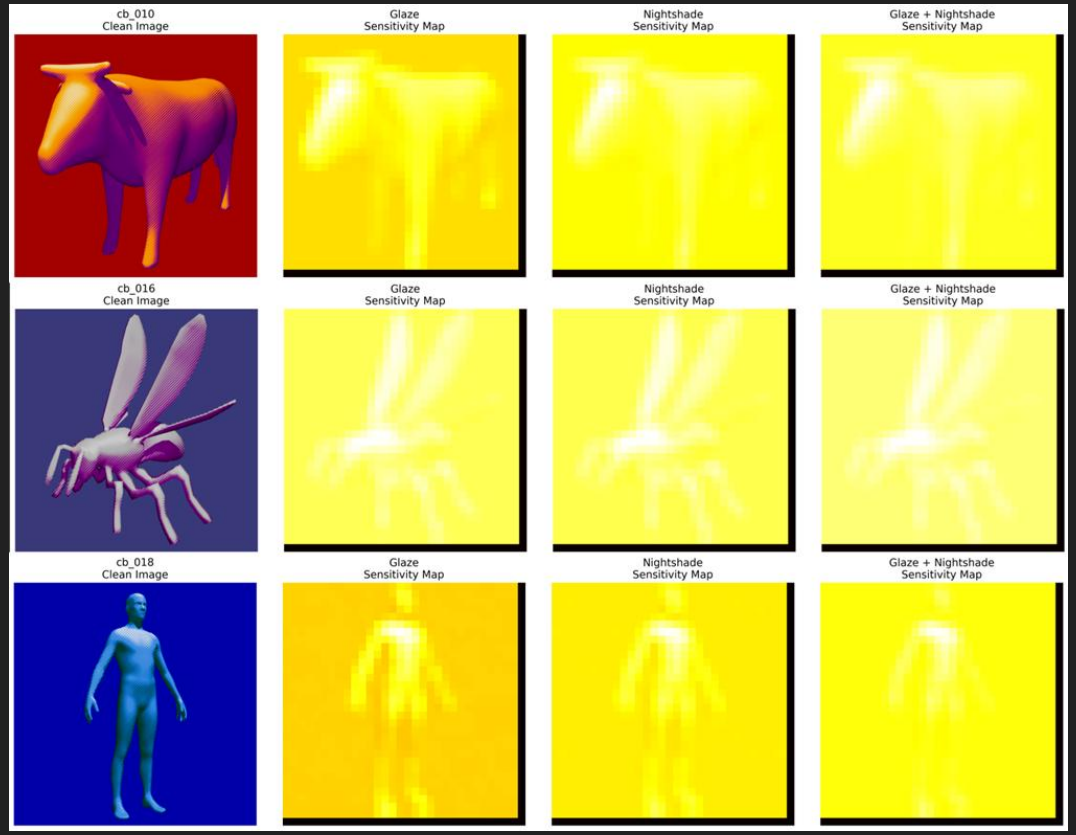


Using this Dataset:

- Spatial sensitivity probed via sliding-window occlusion
- Measures output change under localized perturbation

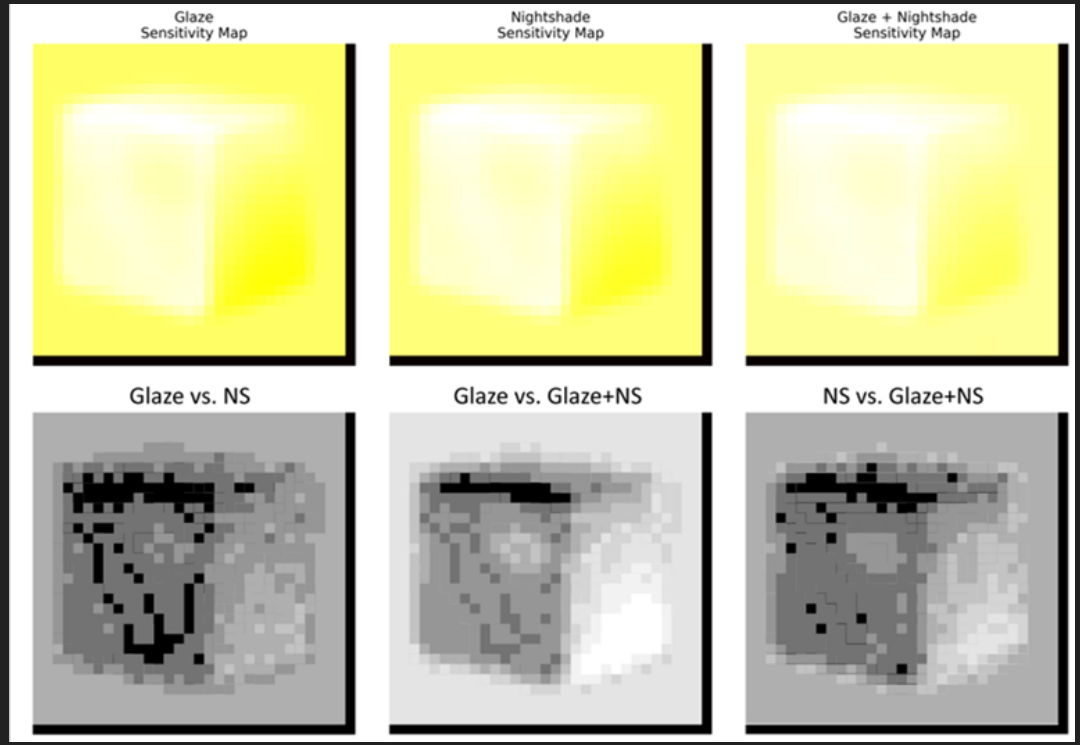
Black-Box Spatial Analysis: Raw Occlusion Limits

- Sensitivity patterns are structurally similar across all perturbations
- Differences appear primarily as tonal, not geometric
- Glaze: more object-localized contrast
- Nightshade: smoother, more globally distributed response



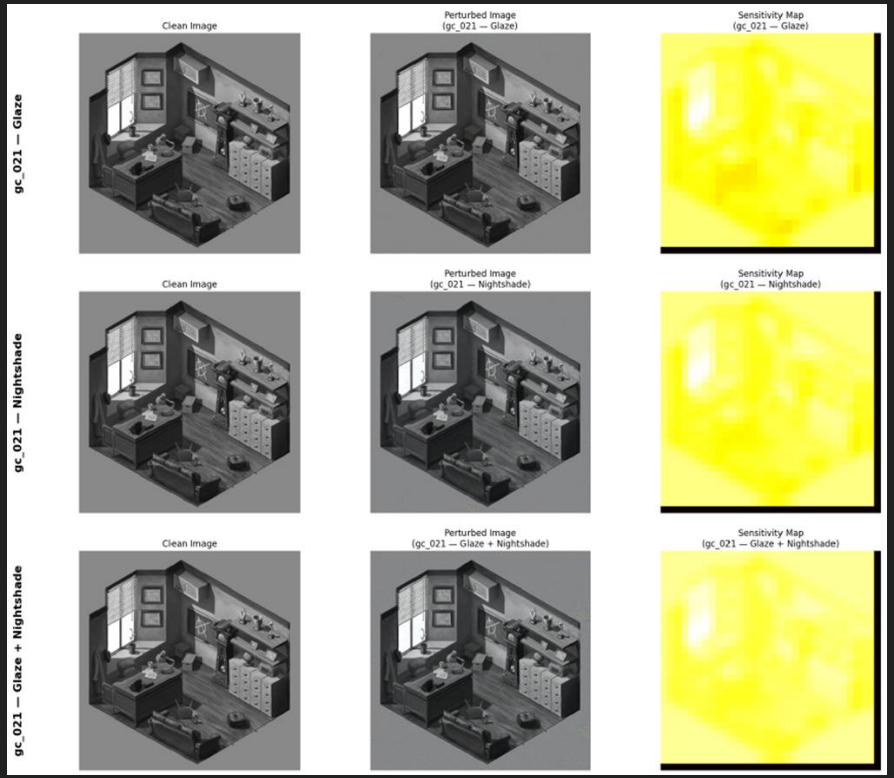
Black-Box Results: Difference Maps Reveal Hidden Structure

- Difference overlays reveal hidden divergences
- Glaze vs. Nightshade diverge on top and right cube faces
- NS→Glaze remains largely Glaze-dominated
- Nightshade vs. NS→Glaze shows broad similarity with localized Glaze structure

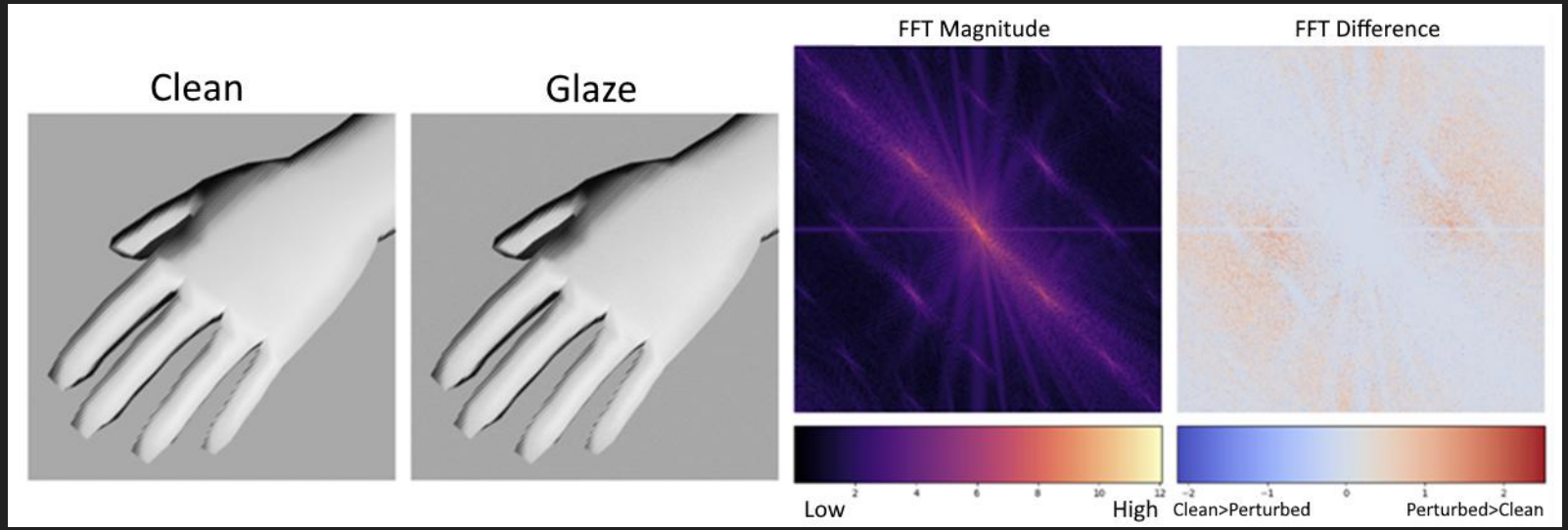


Black-Box Results: Occlusion Sensitivity

- Perturbation influence is **spatially localized, not uniform**
- Nightshade shows **diffuse global sensitivity**
- Glaze shows more object-aligned sensitivity
- Nightshade → Glaze follows Nightshade's spatial pattern
- **Finding:** All perturbations/poison signals remain spatially anchored



Black-Box Analysis #2: Frequency-Domain Analysis



- Analyze perturbations in the **spatial frequency domain**
- Apply **2D Fast Fourier Transform (FFT)** to perturbed images
- Study energy distribution across frequency bands
- Compare Glaze, Nightshade, and NS→Glaze spectra
- Probes structure beyond spatial visibility

Black-Box FFT Processing & Normalization Pipeline

- Compute **2D FFT magnitude** of perturbed images
- Apply **log scaling** for dynamic range compression
- **Center spectra** via FFT-shift
- Radially average to obtain **1D frequency profiles**
- Enables **direct spectral comparison across methods**

Algorithm 3A Log-Magnitude FFT Computation

Given image $g \in [0,1]$, size $H \times W$

$F \leftarrow \text{FFT2}(g)$ ▷ 2D Fast Fourier Transform

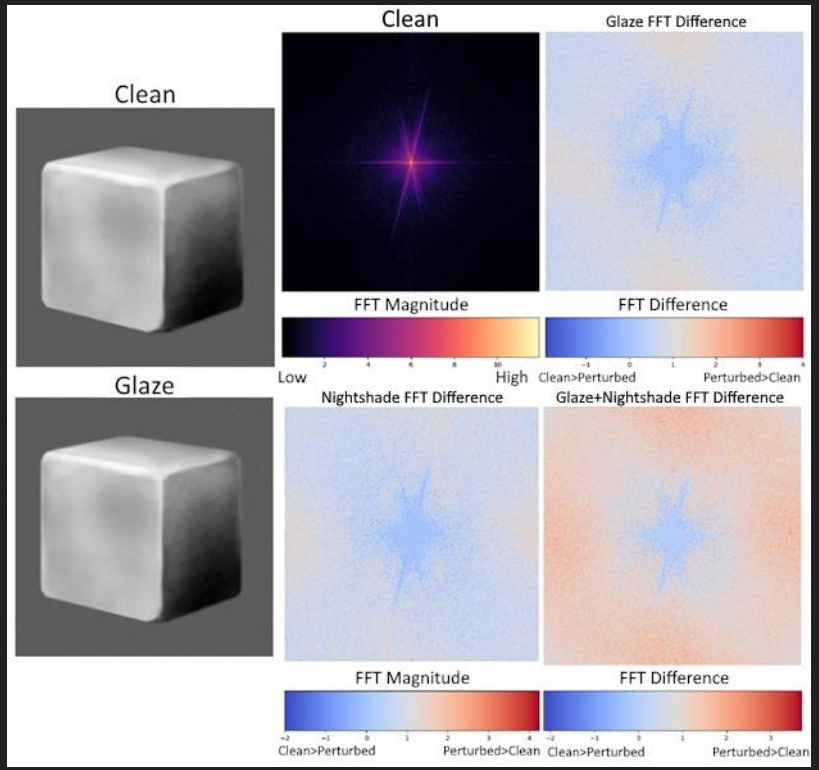
$F \leftarrow \text{FFTShift}(F)$ ▷ Shift DC component to the center

$M \leftarrow \log(1 + |F|)$ ▷ Log-magnitude for dynamic range compression

Return M ▷ Spectral energy representation

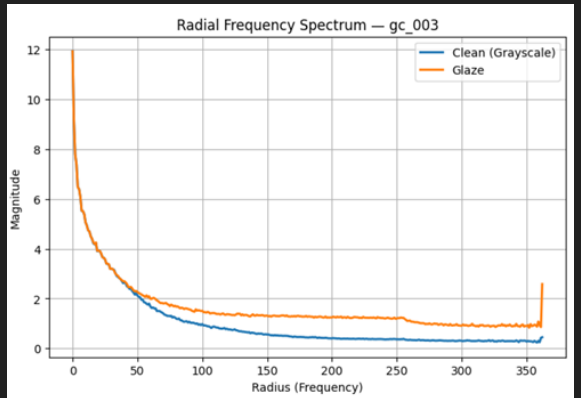
Black-Box Results: FFT – Distinct Spectral Poison Signatures

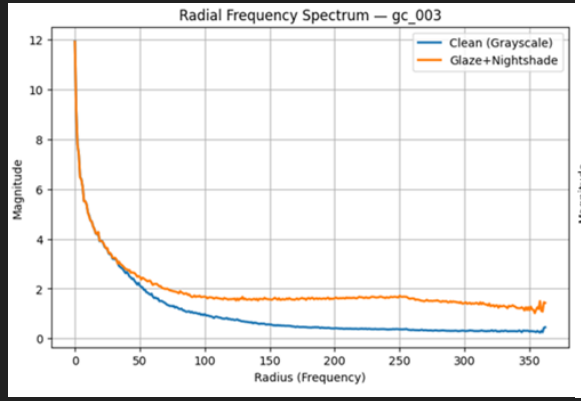
- Glaze concentrates energy in higher spatial frequencies
- Nightshade shows broader low-to-mid frequency distribution
- NS→Glaze exhibits a hybrid but Nightshade-dominant spectrum
- Spectral energy profiles remain stable across image styles
- Confirms poisons differ spectrally, not just spatially

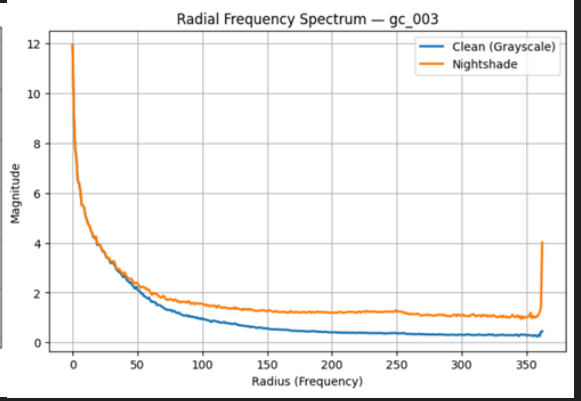


Black-Box Results: Radial Frequency Results (Quantitative Spectral Redistribution)

- All perturbations elevate spectral energy above the clean baseline
- Glaze: smooth, globally coherent upward spectral shift
- Nightshade: stronger low-frequency boost with a sharper high-frequency tail
- NS→Glaze: amplified low–mid frequencies with a regularized high-frequency spike
- **Confirms:** Structured frequency redistribution, not random noise injection







Synthesis: White-Box + Black-Box Picture

VISUALIZATION & INTERFACE DESIGN INNOVATION

WHITE-BOX (Model-Internal Interpretation)

- **Latent Behavior (RQ1, RQ3):**
  Clean and poisoned images form style-driven clusters with poison-specific substructure and clear ordering effects, revealing how perturbations reshape internal representations and influence detectability.
- **LightShed Feature Specialization (RQ2, RQ3):**
  Mid-level encoder layers and sparse channels specialize in reconstructing structured perturbation features, explaining when and why purification succeeds or fails.

BLACK-BOX (Model-Agnostic Signal Analysis)

- **Spatial Structure (RQ1, RQ3):**
  Perturbations are spatially anchored, globally coherent, and aligned with object geometry and background context, directly characterizing signal-level structure and evasion behavior.
- **Frequency Structure (RQ1, RQ2, RQ3):**
  Glaze, Nightshade, and NS→Glaze systematically redistribute existing spectral energy rather than injecting random noise, revealing both detectable band structure and low-entropy signatures exploited by purification.

Unified View: Across white-box and black-box analyses, protection methods act as **structured, low-entropy signal reshaping**, directly explaining both purification effectiveness and adversarial bypass conditions.

Conclusion

- Protection methods inject **structured, low-entropy perturbations**
- These structures are:
  - **Learned and localized internally** (white-box)
  - **Spatially anchored and spectrally organized** (black-box)
- Explains why purification succeeds—and when it fails
- Sequential poisons form hybrid but predictable signal signatures
- Points toward interpretability-driven design of future defenses

Future Work

- Expand to larger datasets and broader artistic style coverage
- Perform cross-model comparisons
  (CLIP-L, OpenCLIP, SigLIP)
- Extend frequency-domain analysis to wavelet-based representations
- Study temporal poisoning dynamics during fine-tuning
- Explore gradient-free surrogate detection models

Authorship and Contributions

Michael Martin

- Conceptualized the research idea and designed detailed methodology
- Developed the full experimental and analytical framework
- Developed and Imeplemented black-box spatial & frequency-domain analysis
- Led methodology development and study design
- Wrote the full research proposal and first-author manuscript

Garrick Chan

- Conducted white-box LightShed neuron and latent analysis
- Conducted t-SNE visualizations based on the designed methodology
- Produced original digital illustrations used in this dataset
- Assisted as co-author on the manuscript

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Thank you!

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