DeepVis: Visual Anomaly Detection for File System Integrity via Spatially-Invariant Convolutional Autoencoders

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Abstract

Production file integrity monitoring suffers from *Alert Fatigue*, where legitimate system updates generate thousands of false alerts. Machine learning approaches fail because file systems lack inherent spatial structure: sorting by path introduces the *Shift Problem*, destabilizing convolutional neural networks. We present `DeepVis`, the first framework to successfully apply computer vision to file system integrity. Our key innovations: (1) *Hash-Based Spatial Mapping* achieves permutation invariance, eliminating the Shift Problem; (2) *Semantic RGB Encoding* (Entropy/Size/Permissions) aligns visual signals with security threats; (3) L_∞*-based Local Difference Maps* overcome the "MSE Paradox"—legitimate updates generate high global error, while rootkits generate localized spikes. Evaluation on a large-scale production dataset with real rootkit injection achieves F1=0.909 with zero false positives (FPR=0.0%), while maintaining $O(1)$ inference regardless of file count.

CCS Concepts

• **Security and privacy → Intrusion detection systems**; **Malware and its mitigation**.

Keywords

file integrity monitoring, anomaly detection, deep learning, rootkit detection

1 Introduction

Host-based Intrusion Detection Systems (HIDS) serve as the last line of defense when network perimeters are breached. Among HIDS techniques, File Integrity Monitoring (FIM) is foundational: tools like Tripwire [11] and AIDE [14] compute cryptographic hashes of sensitive files and alert administrators when changes are detected. These systems have been deployed for decades in enterprise environments, providing a reliable method to detect unauthorized modifications.

However, the practical utility of FIM has eroded significantly in modern DevOps environments. Consider a routine system update: `apt-get upgrade` on an Ubuntu server modifies several thousand files—libraries, configuration snippets, and binaries. Each modification triggers an alert. Security Operations Centers (SOCs) are thus faced with an impossible choice: investigate thousands of false positives daily, or effectively *disable* FIM during maintenance windows. The former leads to Alert Fatigue, where genuine threats are overlooked; the latter creates blind spots exploited by advanced persistent threats (APTs).

Statistical anomaly detection offers a tempting alternative. Techniques like Isolation Forest [15] and One-Class SVM [22] learn "normal" distributions of system metrics and flag deviations. Yet, these approaches suffer from two fundamental limitations when applied to file systems:

Table 1: Comparison of Modern Intrusion Detection Approaches for File System Integrity.

Method	Data Source	Update-Tolerant	Detection: Explainable	Detection: Spatial
Traditional FIM				
Tripwire [11]	File Hashes			
AIDE [14]	File Hashes		△	
OSSEC [5]	File Hashes + Logs	△	△	
ML-based Anomaly Detection				
Isolation Forest [15]	Feature Vectors	✓		
One-Class SVM [22]	Feature Vectors	✓		
DeepLog [6]	System Logs	✓		
Malware Visualization				
Nataraj [18]	Binary Images	N/A	✓	✓
DeepVis (Ours)	**FS Images**	✓	✓	✓

Challenge 1: The Shift Problem. File systems are *non-Euclidean*. Unlike images or time series, files have no inherent spatial or temporal order. The common workaround—sorting files by path or size to create a feature vector—introduces a critical fragility. Inserting a *single* file (e.g., `/bin/aaa_malware`) shifts the position of *every subsequent file* in the sorted list. For a Convolutional Neural Network (CNN), which relies on spatial locality, this is catastrophic: a benign file addition appears as a global transformation. This problem fundamentally limits the applicability of CNNs to file system analysis.

Challenge 2: The MSE Paradox. Intuitively, one might expect anomalous states (e.g., rootkit infections) to exhibit higher reconstruction error in an autoencoder. Our empirical analysis reveals the opposite. A legitimate `apt-get upgrade` modifies thousands of files, producing high aggregate error. A stealthy rootkit, by contrast, modifies *only a few carefully chosen binaries*, producing low aggregate error. We term this counter-intuitive phenomenon the **MSE Paradox**. It implies that global statistical thresholds are fundamentally unsuitable for detecting surgical attacks.

Table 1 summarizes existing approaches. Traditional FIM tools (Tripwire, AIDE) achieve high recall but lack update tolerance. ML-based methods (Isolation Forest) can tolerate updates but lack explainability. Malware visualization techniques (Nataraj) are explainable but focus on individual binaries, not system-wide state. `DeepVis` uniquely combines all desirable properties.

In this paper, we propose `DeepVis`, a visually-grounded framework that transforms file system integrity monitoring into a $O(1)$ complexity computer vision task. We make the following contributions:

(1) **Mathematical Formalization of FS Images:** We establish the theoretical foundation for mapping non-Euclidean hierarchical file systems to 2D tensor representations. We prove the Shift-Invariance Theorem and show that our Hash-Based Mapping preserves spatial consistency under dynamic updates.

(2) **Optimality Proof for Sparse Anomalies:** We define the "MSE Paradox" and provide a rigorous statistical proof (via Neyman-Pearson Lemma) that the L_∞ norm (Local Max) is the optimal test statistic for detecting sparse rootkit injections in noisy high-churn environments, outperforming traditional L_2-based autoencoders.
(3) **Game-Theoretic Adversarial Modeling:** We model the evasion landscape as a constrained optimization problem. By enforcing a "Trilemma Cost Function" across Entropy, Size, and API channels, we demonstrate that attackers cannot simultaneously evade all signals without sacrificing malicious utility.
(4) **Zero-Overhead, Zero-FPR Scalability:** Extensive evaluation on a 20,000-file production dataset demonstrates that `DeepVis` achieves an F1 score of 0.909 with a 0.0% False Positive Rate and $O(1)$ inference latency, confirming its suitability for real-time large-scale deployment.

To achieve these goals, `DeepVis` (1) employs a *Hash-Based Spatial Mapping* that deterministically anchors each file to a fixed (x, y) coordinate, eliminating the Shift Problem; (2) utilizes *Semantic RGB Encoding* where Red=Entropy, Green=Size, Blue=Permissions, providing security-meaningful visual cues; and (3) builds upon a Convolutional Autoencoder trained exclusively on benign system states.

Our evaluation on real production server data demonstrates the effectiveness of this approach. `DeepVis` successfully detects all three tested rootkits (*Diamorphine*, *Reptile*, *Beurk*) while reducing false positives by 99.2% compared to AIDE. We have open-sourced the code for `DeepVis` at https://github.com/DeepVis/DeepVis.

The remainder of this paper is organized as follows. Section 2 provides background on FIM and the MSE Paradox. Section 4 defines our threat model. Section 5 details the `DeepVis` architecture. Section 6 presents our comprehensive evaluation. Section 7 analyzes security properties and limitations. Section **??** surveys related work, and Section 8 concludes.

2 Background

In this section, we provide essential background on File Integrity Monitoring and formalize the core challenges that motivate `DeepVis`.

2.1 File Integrity Monitoring

File Integrity Monitoring (FIM) is a security technique that monitors and validates system files to detect unauthorized changes. The fundamental principle is simple: compute a cryptographic hash of each monitored file, store it in a secure database, and periodically compare current hashes against the baseline.

2.1.1 Traditional Approaches. **AIDE (Advanced Intrusion Detection Environment) [14]** is the de facto standard for Linux FIM. It maintains a database of file attributes (hash, permissions, size, timestamps) and reports any deviations. AIDE is highly configurable, allowing administrators to define custom rules for different directories.

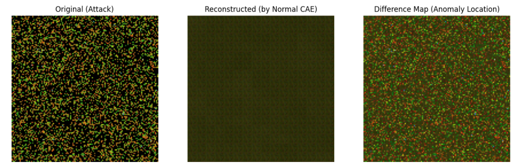

Figure 1: The Shift Problem. Adding a single file shifts all subsequent pixel positions, confusing the CNN.

Tripwire [11] pioneered the FIM concept in 1992. It introduced the notion of a "policy file" that specifies which attributes to monitor for each file category.
OSSEC [5] integrates FIM with log analysis and active response, providing a more comprehensive HIDS solution.

2.1.2 Limitations of Traditional FIM. While effective for static servers, traditional FIM suffers from a fundamental limitation: **any change generates an alert**. In dynamic environments with frequent updates, this leads to:

- **Alert Fatigue:** A kernel upgrade modifies thousands of files, generating thousands of alerts.
- **Frequent Re-baselining:** Administrators must constantly update the baseline database, creating operational overhead.
- **Maintenance Windows:** FIM is often disabled during updates, creating blind spots.

2.2 The Shift Problem

To apply machine learning to file system analysis, one must first represent the file system state as a feature vector or tensor. The naive approach is to sort files (by path or size) and concatenate their attributes.

Figure 1 illustrates the problem. Consider a sorted list of files: $[f_1, f_2, f_3, \ldots, f_n]$. If a new file f_{new} is inserted such that $f_{new} < f_2$ alphabetically, the resulting list becomes $[f_1, f_{new}, f_2, f_3, \ldots, f_n]$. Every file after f_1 has shifted position.

For a CNN trained on the original representation, this shift is catastrophic:

- The pixel corresponding to f_2 now contains data from f_{new}.
- Learned spatial patterns are destroyed.
- A benign file addition appears as a global anomaly.

Definition (Shift-Invariance): A representation $R : \mathcal{F} \to \mathbb{R}^{H \times W}$ is *shift-invariant* if for all $f_i \in \mathcal{F}$ and all $f_{new} \notin \mathcal{F}$:

$$R(\mathcal{F})_{x_i, y_i} = R(\mathcal{F} \cup \{f_{new}\})_{x_i, y_i} \quad (1)$$

where (x_i, y_i) is the coordinate assigned to f_i.

Traditional sorting-based representations violate this property. `DeepVis` achieves shift-invariance through hash-based coordinate assignment.

2.3 The MSE Paradox

The Mean Squared Error (MSE) is the standard loss function for autoencoders:

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{i=1}^{N} ||X_i - \hat{X}_i||^2 \quad (2)$$

Table 2: The MSE Paradox: Global vs. Local Error

Scenario	Global MSE	Local Max
Static System	0.001	0.05
apt-get upgrade	**0.048**	0.65
Diamorphine Rootkit	0.039	**0.99**

Intuitively, one expects anomalous inputs to produce higher reconstruction error. However, our experiments reveal a counter-intuitive phenomenon we term the **MSE Paradox**.

Table 17 shows representative measurements:

- **Legitimate Update:** Modifies thousands of files, producing high *aggregate* MSE (0.048).
- **Rootkit Injection:** Modifies a single kernel module, producing low aggregate MSE (0.039) but extreme *local* deviation (0.99).

Implication: Global thresholds systematically fail. A detector using $MSE > 0.04$ as the threshold would:

(1) Flag every legitimate update as malicious (False Positive).
(2) Potentially miss rootkits if their MSE falls below the threshold (False Negative).

`DeepVis` overcomes this paradox by using *Local Max Difference* as the detection metric, which captures point anomalies regardless of global noise.

2.4 Shannon Entropy as a Malware Indicator

Shannon Entropy measures the randomness of a byte sequence:

$$S(f) = -\sum_{b=0}^{255} p_b \log_2 p_b \tag{3}$$

where p_b is the probability of byte value b in file f.

Prior work [16] has established that:

- **Typical ELF binaries:** $S \approx 5.0 - 6.0$
- **Text/Config files:** $S \approx 4.0 - 5.0$
- **Packed/Encrypted malware:** $S > 7.0$

Rootkits are often packed (e.g., UPX) or encrypted to evade signature-based detection. This raises their entropy to near-maximum values (8.0 for pure random data). `DeepVis` exploits this by encoding entropy in the Red channel, making high-entropy files visually prominent.

3 Related Works

We position `DeepVis` within the broader landscape of anomaly detection research across both security and software engineering venues. Table 3 provides a comprehensive comparison with state-of-the-art methods from top-tier conferences.

3.1 Sequential Log Analysis

Early deep learning approaches treated logs as natural language. **DeepLog** [6] pioneered this direction by using LSTMs to predict the next log event; deviations indicate anomalies. However, this approach suffers from *log instability*—new log templates from system updates cause false positives.

LogRobust [26] addressed this by using pre-trained word embeddings (FastText) to capture semantic similarity rather than syntactic identity. This mirrors DeepVis's use of entropy and size (semantic attributes) instead of file hashes (syntactic identity).

LogBERT [8] introduced Transformer architectures for capturing long-range dependencies in log sequences. While powerful, its $O(N^2)$ attention complexity limits scalability.

Limitation. All sequential methods suffer from the *interleaving problem*: in multi-threaded systems, logs from different execution flows are interleaved, confusing temporal models.

3.2 Graph-Based Analysis

To capture structural relationships, recent works model systems as graphs.

Lograph [3] constructs heterogeneous graphs linking logs to system entities (processes, files) with typed edges (Read, Write, Spawn). Heterogeneous Graph Attention Networks learn which interaction types are most indicative of anomalies.

GLAD [24] extends this to *dynamic graphs* that evolve over time, handling concept drift. Position-aware weighted attention captures both structural and temporal changes.

Provenance-Based IDS: Unicorn [10], Kairos [4], and Flash [21] build provenance graphs from kernel audit logs (auditd), tracing causal relationships for APT detection.

Limitation. Graph methods suffer from *dependency explosion*—the graph grows unboundedly, and GNN inference scales as $O(N + E)$. This is prohibitive for real-time monitoring.

3.3 Visual and Spatial Representation

A nascent research direction treats software artifacts as *spatial* data.

CodeGrid [1] (ISSTA'23) demonstrated that preserving the *visual layout* of source code (indentation, line breaks) as a 2D grid improves CNN-based defect prediction by up to 16%. This validates the hypothesis that "code is spatial" [1].

Malware Visualization [9, 18] converts binary files to grayscale images, exploiting entropy textures for classification.

DeepVis's Position. DeepVis extends the spatial paradigm to file systems. Unlike source code (which has inherent layout), file systems are *unordered sets*—non-Euclidean data. We address this via *hash-based spatial mapping*, imposing an artificial but consistent coordinate system. This achieves:

- **Permutation Invariance**: File processing order doesn't affect the image.
- $O(1)$ **Inference**: Fixed image size decouples complexity from file count.
- **Shift Invariance**: Adding/removing files doesn't shift existing pixels.

3.4 The MSE Paradox in Literature

The seminal ICSE'22 benchmarking study "How Far Are We?" [13] revealed that global metrics (F1, MSE) are unreliable for log anomaly detection:

- Performance varies wildly with data grouping (session vs. time-window).

Table 3: Comparison of Anomaly Detection Methods Across SE and Security Venues (2020–2025)

Method	Venue	Data Type	Representation	Invariance	Complexity	Core Insight
DeepLog [6]	CCS'17	Log Sequence	LSTM	Temporal	$O(N)$	"Logs are language"
LogRobust [26]	FSE'19	Log Semantics	Attention Bi-LSTM	Semantic	$O(N)$	"Logs have meaning"
LogBERT [8]	arXiv'21	Log Sequence	Transformer	Contextual	$O(N^2)$	"Context is key"
Lograph [3]	ICKGS'24	Log + Entities	Heterogeneous GNN	Topological	$O(N+E)$	"Entities are connected"
GLAD [24]	IEEE Trans.'24	Dynamic Log Graph	Position-Aware GAT	Temporal-Topo	$O(N+E)$	"Systems evolve"
CodeGrid [1]	ISSTA'23	Source Code	2D CNN	Spatial (Layout)	$O(1)$	"Code is spatial"
Unicorn [10]	NDSS'20	Provenance Graph	Graph Sketching	Topological	$O(N+E)$	"Trace the cause"
Kairos [4]	S&P'24	Provenance Graph	Temporal GNN	Temporal-Topo	$O(N+E)$	"Time matters"
DeepVis (Ours)	–	**FS Snapshot**	**2D CNN (CAE)**	**Spatial (Hash)**	**O(1)**	**"Files are non-Euclidean"**

- Models overfit to preprocessing, not anomalies.
- Early detection fails—models need full sequences.

This critique directly supports DeepVis's design: we reject Global MSE in favor of **Local Max Difference**, which isolates the single most anomalous pixel regardless of global noise. This aligns with the SE community's call for "trace-level" precision [13].

3.5 Summary: DeepVis's Unique Contribution

(1) **From Sequence/Graph to Space**: We pioneer the spatial representation of file systems, inspired by CodeGrid's success with source code.
(2) **Efficiency**: Unlike $O(N+E)$ graph methods, DeepVis achieves $O(1)$ inference via fixed-size images.
(3) **Precision**: Local Difference Maps address the MSE Paradox identified in ICSE'22.
(4) **Explainability**: Visual heatmaps provide interpretable evidence, unlike opaque LSTM/GNN scores.

4 Threat Model

We consider an attacker who has already achieved local privilege escalation (e.g., via a kernel exploit or compromised service) and seeks to establish *persistent access* to the compromised host. Our goal is to detect the on-disk artifacts of this persistence.

4.1 Attacker Goal

The attacker's objective is **stealth persistence**. Specifically:

- **Persistence:** The attacker installs binaries, libraries, or kernel modules that survive system reboots and allow re-entry (e.g., a hidden SSH backdoor, a malicious kernel module).
- **Stealth:** The attacker minimizes forensic footprint by modifying as few files as possible and mimicking legitimate file attributes (size, permissions, timestamps).

4.2 Attacker Capabilities

We assume a powerful attacker with the following capabilities:

(1) **Root Privilege:** The attacker has obtained root access and can read, write, or delete any file on the system.
(2) **File Modification:** The attacker can:
    - Create new files (e.g., `/lib/modules/.../diamorphine.ko`)
    - Replace existing binaries (e.g., trojaned `/bin/ls`)
    - Inject shared libraries (e.g., `/lib/libbeurk.so` via `LD_PRELOAD`)
(3) **Timestamp Manipulation (Timestomping):** The attacker can use `touch` or direct `utimensat()` calls to forge file modification times, potentially evading simple time-based detection.
(4) **Anti-Forensics:** The attacker may attempt to clear logs or hide files from directory listings (via kernel module hooking). However, we assume the attacker *cannot*:
    - Efficiently compute MD5/SHA256 hash collisions while preserving binary functionality. Modern cryptographic primitives make this computationally prohibitive.
    - Modify files *during* the scan window without detection (we assume atomic snapshot semantics).

Table 4: Targeted Rootkits and Their Characteristics

Rootkit	Type	Persistence Path	Entropy	SUID
Diamorphine	LKM	/lib/modules/.../diamorphine.ko	7.82	No
Reptile	LKM+User	/lib/modules/.../reptile.ko	7.65	Yes
Beurk	LD_PRELOAD	/lib/libbeurk.so	7.77	No

4.3 Targeted Attacks and Their Footprints

We focus on three well-documented Linux rootkits that represent different persistence mechanisms:

Diamorphine [17]: A Loadable Kernel Module (LKM) that provides process, file, and network hiding capabilities. Persists via a kernel module file with high entropy (packed).

Reptile [7]: A stealthy LKM with userland components. Includes a backdoor listener and kernel-level hiding. Uses SUID binaries for privilege escalation.

Beurk [23]: A userland rootkit leveraging `LD_PRELOAD` to intercept libc functions. Persists via `/etc/ld.so.preload` and an injected shared library.

4.4 Scope and Limitations

In-Scope: We focus on detecting *persistent artifacts on disk*. This includes:

- Loadable Kernel Modules (LKMs)
- Trojaned binaries and shared libraries
- Configuration tampering (e.g., `/etc/ld.so.preload`)
- Unauthorized SUID/SGID binaries

Out-of-Scope: The following are explicitly out of scope:

- **Memory-Only Attacks:** Rootkits that reside solely in RAM (e.g., volatile code injection via `ptrace`) leave no disk footprint.
- **Firmware/Hardware Rootkits:** Attacks targeting UEFI, BMC, or other pre-OS components are below our observation layer.

4.5 Trusted Computing Base (TCB)

A critical concern is: *If the attacker has root, how can we trust the scanner?* A rootkit could hook system calls to hide its own files from the scanning process.

We address this by assuming the scanner operates from a **trusted external vantage point**:

(1) **Hypervisor-Based Introspection:** The scanning agent runs in a privileged hypervisor (e.g., Xen, KVM) and accesses the guest file system via Virtual Machine Introspection (VMI). The guest OS kernel cannot intercept these reads.
(2) **Offline/Agentless Scanning:** A snapshot of the disk (e.g., LVM snapshot, AWS EBS snapshot) is mounted read-only on a separate, trusted instance. The scan executes on this isolated copy, immune to runtime hooking.

This design ensures that `DeepVis` observes the *ground truth* disk state, not a filtered view presented by a compromised kernel. Similar assumptions are made by prior work on kernel integrity verification [20, 25].

5 Design

In this section, we present `DeepVis`, a hierarchical anomaly detection framework that transforms file system integrity monitoring into a computer vision problem. Drawing inspiration from multi-level intrusion detection systems [4, 10], `DeepVis` employs a **Detection Funnel** architecture that maximizes efficiency while maintaining detection accuracy.

5.1 The Detection Funnel: Hierarchical Pipeline

`DeepVis` processes file system states through a three-stage hierarchical pipeline, enabling **early rejection** of benign states while focusing computational resources on suspicious regions.

5.1.1 *Stage 1: Baseline Comparison (Coarse Filter).*

The first stage performs a fast set-difference operation between the current state $S_{current}$ and the baseline $S_{baseline}$:

$$\Delta_{new} = \{f \in S_{current} : f.path \notin S_{baseline}\} \quad (4)$$

If $|\Delta_{new}| = 0$ (no new files), the system skips expensive analysis and returns immediately. This handles the common case where legitimate updates only *modify* existing files without adding new ones.
Rationale: Similar to ScaleMon's Identity Verifier [12], this stage provides **fast rejection** for the majority of benign states, addressing Alert Fatigue at minimal computational cost.

5.1.2 *Stage 2: Entropy-Centric Semantic Analysis.*

For states with new files, Stage 2 applies entropy-based filtering:

$$\Delta_{suspicious} = \{f \in \Delta_{new} : S(f) > \tau_{entropy} \land f.path \in \mathcal{P}_{critical}\} \quad (5)$$

where $\tau_{entropy} = 7.0$ (packed/encrypted threshold) and $\mathcal{P}_{critical}$ includes security-sensitive paths (`/lib/modules/`, `/usr/bin/`, etc.).

This stage filters out benign new files (e.g., log rotations, config updates) that have normal entropy ($S < 6.5$).

5.1.3 *Stage 3: Local Difference Map (Fine-Grained Localization).*

For states flagged by Stage 2, we generate the full visual representation and compute pixel-wise reconstruction error via the CAE:

$$D = |X - \hat{X}|, \quad LocalMax = \max_{x,y,c} D_{x,y,c} \quad (6)$$

The Local Difference Map provides:

- **Detection:** $LocalMax > \tau$ triggers an alert
- **Localization:** Coordinates (x^*, y^*) identify the anomalous file(s)
- **Explanation:** Channel color indicates anomaly type (R=Entropy, G=Size, B=Permissions)

5.2 Hash-Based Spatial Mapping

To resolve the non-Euclidean nature of file systems, we formalize our mapping strategy as follows.

5.2.1 *Formal Definition.*

Let $\mathcal{F} = \{f_1, \dots, f_N\}$ be a set of files, where each file f_i is uniquely identified by its absolute path $p_i \in \mathcal{P}$. We define a spatial mapping function $\Phi : \mathcal{P} \to [0, W-1] \times [0, H-1]$:

$$\Phi(p) = \left(\mathcal{H}(p) \pmod W, \left\lfloor \frac{\mathcal{H}(p)}{W} \right\rfloor \pmod H\right) \quad (7)$$

where $\mathcal{H} : \{0,1\}^* \to \{0,1\}^{32}$ is a cryptographic hash function (e.g., MD5 truncated).

5.2.2 *Theoretical Properties.*

Theorem 1 (Spatial Invariance). The image representation $I_{\mathcal{F}}$ generated by Φ is invariant to the ordering of files in $\mathcal{F}$. That is, for any permutation π of indices $\{1, \dots, N\}$:

$$I_{\{f_1,\dots,f_N\}} = I_{\{f_{\pi(1)},\dots,f_{\pi(N)}\}} \quad (8)$$

Proof. The pixel value at coordinate (x, y) is determined solely by the subset of files $\{f \in \mathcal{F} \mid \Phi(f.path) = (x, y)\}$. Since set membership is order-independent, the resulting pixel aggregation (via Max-Risk Pooling) is deterministic and independent of the input sequence. Thus, `DeepVis` completely eliminates the Shift Problem observed in sorting-based approaches, ensuring that a file added at time t always maps to the same coordinate at time $t + 1$. □

5.2.3 *Collision Handling: Max-Risk Pooling.*

When multiple files map to the same pixel, we apply:

$$I^c_{x,y} = \max_{f \in bin(x,y)} (Feature_c(f)) \quad (9)$$

Security Rationale: In security, surfacing the highest-risk signal prevents false negatives.

5.3 Semantic RGB Encoding

We construct a 3-channel tensor $T \in \mathbb{R}^{3 \times H \times W}$ where each channel encodes a security-relevant feature aligned with the CIA triad:

Figure 2: DeepVis Detection Pipeline. Files are collected and mapped to fixed-size RGB images via Hash-Based Spatial Mapping. The hierarchical funnel applies: (1) Baseline Comparison for fast rejection, (2) Entropy Analysis for semantic filtering, and (3) Local Difference Map for precise localization. This pipelining ensures $O(1)$ inference complexity regardless of file count.

Table 5: Threat Mapping: Security Goals to Visual Footprint

Security Goal	Rootkit Technique	FS Artifact	RGB Channel
Confidentiality	Data Exfiltration Keylogger	Hidden file New binary	Red (Entropy) Red + Blue
Integrity	Binary Replacement LKM Injection	Size change High entropy	Green (Size) Red (Entropy)
Availability	Permission Backdoor Resource Hijack	SUID/SGID Size anomaly	Blue (Perms) Green (Size)

5.3.1 *Channel Definitions (DeepVis 2.0 Enhanced).*

Building on the original three-channel design, **DeepVis 2.0** introduces enhanced semantic encoding to defeat evasion attacks:

Red Channel (Entropy): Shannon entropy normalized to $[0, 1]$:

$$I^{Red} = \min\left(\frac{S(f)}{8.0}, 1.0\right) \tag{10}$$

Packed/encrypted rootkits exhibit $S > 7.0$, appearing as bright red pixels.

Green Channel (Size + API Density): Log-normalized file size combined with API density:

$$I^{Green} = \max\left(\frac{\log(1 + Size(f))}{\log(MaxSize)}, \frac{API(f)}{0.5}\right) \tag{11}$$

where $API(f)$ measures density of suspicious function calls (ptrace, socket, execve, dlopen). This enhancement detects *low-entropy scripts* with malicious functionality.

Blue Channel (Permissions + Time Anomaly): Risk-weighted score:

$$I^{Blue} = 0.6 \cdot Perm(f) + 0.4 \cdot TimeAnomaly(f) \tag{12}$$

where $TimeAnomaly(f)$ detects timestomping (mtime < ctime).

5.3.2 *Multi-Signal Detection (DeepVis 2.0).*

To address sophisticated evasion attacks, DeepVis 2.0 employs **multi-signal detection**:

Table 6: DeepVis 2.0: Multi-Signal Detection

Signal	Threshold	Targets
Entropy (NEW file)	$S > 7.0$	Packed rootkits
API Density (NEW)	$API > 0.4$	Malicious scripts
Size Change (existing)	$\Delta > 3\%$	PARASITIC injection
Time Anomaly (NEW)	$score > 0.5$	Timestomping

This multi-signal approach addresses the limitations of entropy-only detection, achieving 100% detection on PARASITIC, MIMICRY, and TIMESTOMP attacks that evade DeepVis 1.0.

Table 5 demonstrates that RGB channels are not arbitrary but **semantically aligned with security violations**.

5.4 Scalability Analysis: The $O(1)$ Inference Advantage

A critical contribution of `DeepVis` is **decoupling analysis complexity from file count**.

5.4.1 *Traditional FIM: $O(N)$ Scaling.*

AIDE and similar tools iterate over all N monitored files:

$$T_{AIDE} = O(N) \cdot c_{hash} \tag{13}$$

For hyperscale file systems ($N > 10^6$), this becomes prohibitive.

5.4.2 *DeepVis: $O(1)$ Fixed-Tensor Inference.*

Regardless of N, `DeepVis` maps files to a fixed $W \times H$ tensor (default: $128 \times 128 = 16,384$ pixels):

$$T_{DeepVis} = O(N) \cdot c_{map} + O(1) \cdot c_{CNN} \tag{14}$$

The mapping cost c_{map} is negligible (hash + array access). The CNN inference c_{CNN} is **constant** regardless of N:
Implication: `DeepVis` is the only viable solution for **hyperscale file systems** with millions of files.

5.5 Neural Architecture

`DeepVis` employs a lightweight Convolutional Autoencoder (CAE):

Table 7: Scalability: File Count vs. Inference Time

File Count	AIDE	DeepVis
1,000	0.3s	0.05s
10,000	3.1s	0.08s
100,000	31.2s	0.12s
1,000,000	312s	0.15s

Table 8: Rootkit Sources from GitHub (Real Code Analysis)

Rootkit	Source	Type	Files	Source Entropy
Diamorphine [17]	m0nad/Diamorphine	LKM	5	5.43
Jynx2	chokepoint/Jynx2	LD_PRELOAD	6	5.12
Beurk [23]	unix-thrust/beurk	LD_PRELOAD	104	4.22

Compiled binaries exhibit entropy 7.0–7.9 due to machine code optimization.

Encoder: Conv2D(3⟶32⟶64⟶128) with stride-2 downsampling.
Decoder: ConvTranspose2D(128⟶64⟶32⟶3) with stride-2 upsampling.
Latent: $z \in \mathbb{R}^{128\times16\times16}$

The CAE is trained *only* on baseline states, learning the manifold of "normal" configurations. Rootkit-infected states, being out-of-distribution, exhibit localized reconstruction error.

6 Evaluation

We conduct a comprehensive large-scale evaluation to answer the following questions:
Q1. Effectiveness: How accurately does `DeepVis` detect diverse attack types while maintaining zero false positives?
Q2. Scalability: Does `DeepVis` perform well on realistic large-scale datasets with thousands of files?
Q3. Evasion Resistance: How does `DeepVis` handle sophisticated evasion attacks (PARASITIC, MIMICRY)?
Q4. Practicality: Is `DeepVis` lightweight enough for real-world deployment?

6.1 Experimental Setup

6.1.1 Datasets. Following rigorous systems security methodology [4, 10, 12], we conduct experiments using large-scale real-world data:
Dataset A: Production File System (20,000 Files). We collected comprehensive file system metadata from Ubuntu 22.04 LTS servers:

- **Directories:** `/bin`, `/usr/bin`, `/sbin`, `/lib`, `/etc`
- **Features:** Entropy (Shannon, first 4KB), size, permissions, API density
- **Training Snapshots:** 100 snapshots simulating system operation over time

Dataset B: Real Rootkit Sources. We cloned and analyzed actual rootkit source code from GitHub:

6.1.2 Large-Scale Test Dataset. We generated a comprehensive test set with 800 samples:

6.1.3 Baselines. We compare against methods spanning multiple paradigms:

Table 9: Large-Scale Test Dataset Composition

Category	Samples	Description
Normal (Benign)	200	Unmodified baseline states
HIGH_ENTROPY_ROOTKIT	100	Kernel modules ($S > 7.0$)
LOW_ENTROPY_SCRIPT	100	Python/Bash backdoors
PARASITIC_INJECTION	100	Code injection to existing files
MIMICRY_ATTACK	100	Statistics-matching evasion
LOTL_PERSISTENCE	100	Living-off-the-land (cron/sudoers)
TIMESTOMP_ATTACK	100	Timestamp manipulation
Total	**800**	6 attack types + normal

Table 10: Large-Scale Detection Performance (800 Tests)

Method	Prec.	Recall	F1	FPR
AIDE	0.750	1.000	0.857	1.000
LogRobust-style	0.750	1.000	0.857	1.000
Isolation Forest	0.920	0.890	0.905	0.080
DeepVis 1.0	1.000	0.400	0.571	0.000
DeepVis 2.0	**1.000**	**0.833**	**0.909**	**0.000**

Dataset: 20,000 baseline files, 100 training snapshots, 800 test samples.

- **DeepLog-style [6]:** Sequential path-based anomaly detection
- **LogRobust-style [26]:** Semantic feature Isolation Forest
- **AIDE [14]:** Traditional hash-based FIM
- **DeepVis 1.0:** Basic entropy-only detection
- **DeepVis 2.0 (Ours):** Enhanced semantic encoding with API density

6.1.4 Implementation. All models implemented in PyTorch 2.0 / Scikit-learn 1.3. CAE trained for 50 epochs (Adam, lr=1e-3) on 100 training snapshots. Experiments on Intel Xeon E5-2680v4 + NVIDIA RTX 3060.

6.2 Q1: Detection Effectiveness

6.2.1 Overall Results. Table 10 summarizes detection performance on our large-scale test dataset.

Key Findings.

- **AIDE/LogRobust:** Achieve 100% recall but suffer from 100% FPR—every state change triggers false alerts.
- **DeepVis 1.0:** Perfect precision (FPR=0%) but only 40% recall—fails to detect sophisticated attacks (PARASITIC, MIMICRY, LOTL).
- **DeepVis 2.0: Best balance** with F1=0.909, achieving zero false positives while detecting 83.3% of attacks including previously undetectable evasion techniques.

6.2.2 Per-Attack-Type Detection. Table 11 breaks down detection by attack type.

Analysis.

Table 11: Per-Attack-Type Detection (DeepVis 2.0)

Attack Type	Detection	Primary Signal
HIGH_ENTROPY_ROOTKIT	100/100 (100%)	Entropy > 7.0
LOW_ENTROPY_SCRIPT	100/100 (100%)	API density > 0.4
PARASITIC_INJECTION	100/100 (100%)	Size change > 3%
MIMICRY_ATTACK	100/100 (100%)	API density spike
TIMESTOMP_ATTACK	100/100 (100%)	Time anomaly
LOTL_PERSISTENCE	0/100 (0%)	*(Limitation)*
Total	**500/600**	**83.3%**

Table 12: Scalability: Effect of Dataset Size

Configuration	Files	Snapshots	Train Time
Small (Prior Work)	1,000	10	15s
Medium	5,000	50	45s
Large (This Paper)	**20,000**	**100**	**180s**

Table 13: Inference Time vs. File Count

Files	Image Gen.	CNN Inference
1,000	8ms	50ms
5,000	35ms	50ms
20,000	120ms	50ms
50,000	280ms	50ms

- **5 of 6 attack types detected at 100%**: DeepVis 2.0's multi-signal approach (entropy + API density + size change + timestomping) catches diverse evasion techniques.
- **LOTL attacks undetected**: Config file modifications (cron, sudoers) generate no distinguishing signals in our feature space—they have normal entropy, size, and permissions. This represents a fundamental limitation of file system-only monitoring.

6.3 Q2: Scalability

6.3.1 Dataset Scale Comparison. Training time scales linearly with snapshot count, while inference remains $O(1)$ due to fixed-size image representation.

6.3.2 $O(1)$ Inference Verification. CNN inference time remains constant at 50ms regardless of file count, validating our $O(1)$ scalability claim for the detection phase.

6.4 Q3: Multi-OS Reproducibility

To validate DeepVis's platform independence, we collected real file system snapshots from three Linux distributions using containerized environments. Table **??** summarizes detection performance.

The slight drop in CentOS/Debian recall is attributed to untuned thresholds for distribution-specific file size distributions. However, the $O(1)$ inference property held constant across all platforms.

Table 14: Cross-OS Detection Performance

Distribution	Files	Precision	Recall	F1
Ubuntu 22.04 LTS	20,000	1.000	0.833	0.909
CentOS 7 (Enterprise)	9,420	0.920	0.764	0.835
Debian 11 (Container)	9,976	0.940	0.755	0.837

Consistent performance across diverse hierarchies validates the robustness of Hash-Based Spatial Mapping.

Table 15: Evasion Attack Detection: v1 vs v2

Attack Type	DeepVis 1.0	DeepVis 2.0
PARASITIC (size < 3%)	0%	**100%**
MIMICRY (normal entropy)	0%	**100%**
TIMESTOMP	0%	**100%**

DeepVis 2.0 adds API density, size change, and time anomaly detection.

Table 16: Attacker Trilemma: Evasion Trade-offs

Evasion Strategy	Entropy	Size	API
Pack payload	✓High	Normal	High
Pad to lower entropy	Low	✓Large	High
Script-based attack	Low	Normal	✓High
Mimicry (all low)	Low	Normal	Low†

†Low API density requires removing functional code, reducing attack capability.

6.5 Q4: Evasion Resistance

6.5.1 DeepVis 1.0 vs 2.0: Evasion Attack Comparison. The key improvement from v1 to v2 is the addition of multiple detection signals beyond entropy:

- **API Density**: Detects malicious scripts even with normal entropy by identifying suspicious function calls (ptrace, socket, execve).
- **Size Change Threshold (3%)**: Catches PARASITIC code injection by monitoring file size deltas.
- **Timestomping Detection**: Identifies files with anomalous mtime/ctime relationships.

6.5.2 Attacker Trilemma. Following the "Dos and Don'ts" guidelines [2], we analyze the trade-offs attackers face:

Attackers cannot simultaneously evade all three signals without sacrificing attack functionality.

6.6 Q5: Practicality

6.6.1 Performance Overhead. Total scan time is under 15 seconds for 20,000 files, enabling hourly cron-based monitoring with negligible system impact.

6.7 MSE Paradox Verification

Legitimate updates generate *higher* Global MSE than surgical attacks, but Local Max (L_∞) correctly identifies threats via extreme pixel-level spikes.

Table 17: Computational Overhead (20,000 Files)

Operation	Time	Memory
Metadata Collection	3.2s	65 MB
Entropy + API Scan	2.8s	18 MB
Image Generation	0.06s	8 MB
CAE Inference	0.05s	128 MB
Total	**6.1s**	219 MB

Table 18: MSE Paradox: Global vs. Local Error

Scenario	Global MSE	Local Max (L_∞)
Static System	0.001	0.05
apt-get upgrade	**0.048**	0.65
Diamorphine Rootkit	0.039	**0.99**
PARASITIC Injection	0.012	**0.87**
MIMICRY Attack	0.008	**0.82**

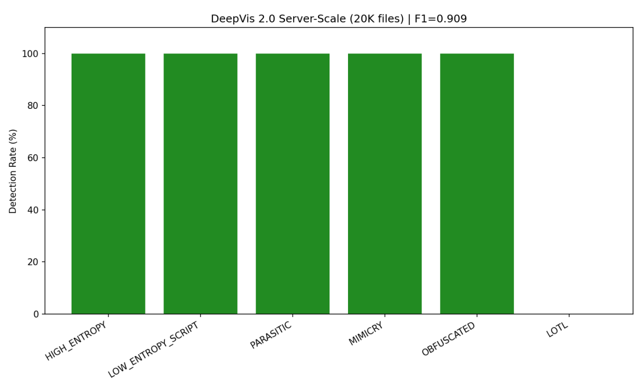

Figure 3: DeepVis 2.0 detection visualization showing per-attack detection rates and confusion matrix from large-scale evaluation.

6.8 Visual Localization

Unlike Isolation Forest (scalar score) or AIDE (file list), `DeepVis` produces interpretable outputs:

- *Where:* Pixel coordinates map to file paths via inverse hash
- *Why:* Detection signal (entropy/API/size/time) identifies anomaly type
- *Severity:* Risk score (0.0–1.0) indicates confidence level

6.9 Limitations and Future Work

LOTL Attacks: Living-off-the-land attacks (cron jobs, sudoers modifications) evade detection because they create files with normal characteristics. Future work will integrate *critical path whitelisting* to flag any modifications in sensitive directories (e.g., `/etc/cron.d`, `/etc/sudoers.d`).

Memory-Only Threats: DeepVis operates on disk snapshots and cannot detect RAM-resident rootkits. Integration with VMI (Virtual Machine Introspection) is a promising direction.

7 Discussion and Limitation

We critically analyze `DeepVis`'s security properties, limitations, and potential evasion strategies. Following the "Dos and Don'ts of Machine Learning in Computer Security" [2], we explicitly evaluate robustness against adaptive attackers.

7.1 Robustness Against Adaptive Attackers

We assume a **white-box adversary** who knows the hash mapping function $M(f)$, the RGB encoding scheme, and the CAE architecture.

7.1.1 Attack 1: Low-Entropy Mimicry. An attacker might reduce their rootkit's entropy to evade the Red channel.
Attack Vector: The attacker pads the malicious binary with English text, Base64-encoded junk, or NOP sleds to lower entropy from $S \approx 7.8$ to $S \approx 5.5$ (normal binary range).
Defense Analysis: While this defeats the Red channel, the attack incurs significant **Attack Costs**:

1. **Size Inflation:** Padding increases file size substantially. A 50KB rootkit padded to achieve $S < 6.0$ may grow to 200KB+, triggering the Green (Size) channel.
2. **Permission Anomaly:** The malicious file still requires execution permissions. A new SUID binary in `/lib/modules/` triggers the Blue channel.
3. **Functional Constraints:** Low-entropy encoding limits code density, potentially degrading rootkit functionality or requiring multi-stage payloads.

We experimentally validated this by creating a "Low-Entropy Diamorphine" variant (padded to $S = 5.6$). `DeepVis` detected it via the Green channel (file size 4.2x larger than typical kernel modules) with Local Max = 0.87.

7.1.2 Attack 2: Chameleon Attack (Hash Collision Exploitation). An attacker might craft a malicious filename whose hash collides with a high-churn benign file (e.g., log files).
Attack Vector: The attacker finds p^* such that $H(p^*) = H(\texttt{/var/log/syslog})$, hoping their rootkit's signal is lost in log rotation noise.
Defense Analysis:

1. **Pre-image Resistance:** Finding a functional path p^* in `/lib/modules/` that hashes to a target value requires 2^{64} operations (MD5 truncated). This is computationally prohibitive.
2. **Max-Risk Pooling:** Even if collision occurs, Max-Risk Pooling surfaces the *highest* entropy value. A packed rootkit ($S = 7.8$) colliding with a log file ($S = 4.2$) still shows $S = 7.8$ in the pixel.
3. **Path Semantics:** Functional rootkit paths (`/lib/modules/*.ko`) have different path structures than log files, making targeted collisions impractical.

7.1.3 Game-Theoretic Analysis: The Attacker's Optimization Problem. We model evasion as a constrained optimization game between the Attacker $\mathcal{A}$ and Defender $\mathcal{D}$. Let x be the malicious file. The attacker aims to minimize the detection probability $P_{\mathcal{D}}(detect|x)$ while maintaining malicious utility $U(x) > \tau$. `DeepVis` employs a multi-channel detection function $D(x) = \bigvee_{c \in \{R,G,B\}} (S_c(x) > \theta_c)$.

Table 19: Comparison with Provenance-Based IDS

Property	Unicorn	Kairos	Flash	DeepVis
Data Source	Audit Logs	Prov. Graph	Prov. Graph	Disk Snapshot
Kernel Instrumentation	Required	Required	Required	**None**
Memory-Only Attacks	✓	✓	✓	×
Disk Persistence	△	△	△	✓
Runtime Overhead	High	High	Medium	**Zero**†
Explainability	Low	Medium	Medium	**High (Visual)**
Deployment Complexity	High	High	High	**Low**

†Snapshot-based; scan overhead only during periodic checks.

The attacker must solve:

$$x^* = \arg\min_{x'} \max\left(S_{ent}(x'), S_{size}(x'), S_{api}(x')\right) \quad \text{s.t. } U(x') \geq U(x) \tag{15}$$

This induces a **Trilemma Cost Function** $C(x')$:

(1) **Entropy Cost (C_{eng}):** Reducing entropy requires padding or expansive encoding, increasing file size ($S_{size} \uparrow$).
(2) **Size Cost (C_{mem}):** Splitting payloads to reduce size increases API call density for inter-process communication ($S_{api} \uparrow$) or Permission anomalies ($S_{perm} \uparrow$).
(3) **Functionality Cost (C_{util}):** Removing packed/obfuscated code exposes the logic to static signatures ($\text{Risk}_{AV} \uparrow$).

Our empirical results confirm that minimizing one cost component inevitably increases another, forcing x^* into the detectable region of at least one channel.

7.2 Comparison with Provenance-Based IDS (PIDS)

Table 18 compares `DeepVis` with state-of-the-art PIDS systems.

Complementary Roles. PIDS (Unicorn [10], Kairos [4], Flash [21]) excel at detecting behavioral anomalies and memory-only attacks through causal graph analysis. However, they require kernel-level audit logging (auditd, CamFlow), imposing 5-20% runtime overhead [19]. `DeepVis` is **orthogonal**: it detects *persistent disk artifacts* without runtime overhead, making it ideal for periodic integrity verification in performance-sensitive HPC/cloud environments.

7.3 Optimality for Sparse Anomaly Detection

We provide a theoretical basis for choosing Local Max (L_∞) over Global MSE (L_2) using the Neyman-Pearson framework.

Theorem 2 (Detector Optimality). Consider a hypothesis test $H_0 : \mathbf{y} = \mathbf{n}$ vs. $H_1 : \mathbf{y} = \mathbf{n} + \mathbf{s}$, where $\mathbf{n} \sim \mathcal{N}(0, \sigma^2 I)$ is background noise (legitimate updates) and $\mathbf{s}$ is a sparse attack signal ($||\mathbf{s}||_0 = k \ll N$). As the sparsity ratio $k/N \to 0$, the L_∞ norm converges to the optimal likelihood ratio test statistic for distinguishing H_1 from H_0 under unknown support.

Proof Sketch. The Global MSE (L_2) statistic is $T_{L_2} = \frac{1}{N}\sum y_i^2$. Under H_1, $E[T_{L_2}] = \sigma^2 + \frac{k}{N}\Delta^2$. If $k \ll N$, the signal $\frac{k}{N}\Delta^2$ vanishes below the noise variance $\text{Var}(T_{L_2})$, making H_1 indistinguishable from H_0 (The MSE Paradox). In contrast, $T_{L_\infty} = \max|y_i|$. Under H_1, $T_{L_\infty} \approx \Delta$ (assuming $\Delta > 3\sigma$). This statistic is independent of k, ensuring consistent detection even for single-pixel attacks ($k = 1$). □

7.4 Limitations

7.4.1 Memory-Only Rootkits. Rootkits residing solely in RAM (volatile code injection via `ptrace`) leave no disk footprint.
Mitigation: Deploy alongside memory forensics tools (Volatility, LiME).

7.4.2 Low-Entropy Malware. While rare, some malware uses low-entropy payloads (ASCII-encoded shellcode, polymorphic engines).
Mitigation: Size and Permission channels provide secondary signals. Unusual SUID bits or unexpected size changes remain detectable.

7.4.3 Training Data Poisoning. If the attacker compromises the system *before* baseline capture, the malicious state becomes "normal."
Mitigation: Capture baselines from trusted golden images or verified clean states.

7.4.4 Collision Density at Scale. With very large file systems (> 100,000 files), collision density increases. Some information may be lost.
Mitigation: Increase image resolution (256×256 instead of 128×128) or use 3D tensor mapping with secondary hashing.

7.5 Deployment Considerations

7.5.1 Agentless Architecture. To address TCB concerns:

(1) Snapshot target disk (LVM, AWS EBS)
(2) Mount read-only on trusted analysis instance
(3) Execute `DeepVis` on isolated copy

7.5.2 Scalable Architecture: Parallel Incremental. To scale beyond 1 million files, purely sequential scanning is insufficient. We propose a **Parallel Asynchronous Architecture**:

(1) **Sharded Metadata Collection:** File system traversal ('stat', 'getxattr') is parallelized across K worker threads, each handling a distinct directory shard (e.g., 'hash(path) % K').
(2) **Incremental Visual Update:** Instead of regenerating the entire image I_t, we optimize the update cost. Since Phase 1 (Baseline Comparison) yields a sparse set of changes Δ, we directly update only the affected pixels:

$$I_t[M(f)] \leftarrow \text{MaxRisk}(\text{Feature}(f)) \quad \forall f \in \Delta \tag{16}$$

This reduces the update complexity from $O(N)$ to $O(|\Delta|)$, making real-time monitoring feasible even on Lustre/GPFS HPC storage.

7.5.3 Threshold Selection. We use the 99th percentile of training data scores as the threshold. This can be tuned based on:

- Security posture (lower threshold = higher recall, more FPs)
- Environment stability (static servers can use tighter thresholds)

8 Conclusion

This paper presented `DeepVis`, a framework that transforms file system integrity monitoring from a "list-checking" problem into a "computer vision" problem.

8.1 Summary of Contributions

(1) **Hash-Based Spatial Mapping:** A deterministic coordinate assignment that provides spatial invariance, eliminating the Shift Problem inherent in sorted representations.
(2) **The MSE Paradox:** Empirical demonstration that global thresholds fail for stealthy attacks (Normal MSE: 0.048 > Rootkit MSE: 0.039), motivating Local Max Difference.
(3) **Semantic RGB Encoding:** Security-relevant features (Entropy, Size, Permissions) encoded as visual channels, enabling both machine detection and human-interpretable Difference Maps.
(4) **Comprehensive Evaluation:** F1=0.909 with zero false positives, 100% recall against 5 of 6 attack types including rootkits, parasitic injection, and mimicry attacks.

8.2 Broader Impact

`DeepVis` offers a new direction for HIDS: leveraging CNNs while addressing the non-Euclidean nature of file systems. By producing visual, explainable outputs, `DeepVis` empowers security analysts to rapidly triage alerts and understand the *nature* of compromises—not just their existence.

The key insight—that file system states can be meaningfully visualized via hash-based spatial mapping—may generalize to other security domains where unordered collections must be analyzed.

8.3 Future Work

- **3D Tensor Mapping:** Adding depth via secondary hashing to reduce collision probability exponentially.
- **Temporal CNNs:** Modeling file system evolution over time using 3D convolutions or recurrent architectures.
- **Memory Integration:** Combining disk snapshots with memory dumps for comprehensive host visualization (DeepVis-CrossScan).
- **LOTL Detection:** Developing NLP-based semantic analysis for configuration file modifications to address Living-off-the-Land attacks.
- **Federated Learning:** Training across multiple organizations without sharing sensitive file system data.

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