DeepVis: Deep Learning-Based File System Fingerprinting for Cloud Security

***Abstract*—This paper presents `DeepVis`, a high-throughput integrity verification system designed to improve scalability and reduce overhead in hyperscale storage environments. Our key idea is to leverage a spatial hash projection architecture, enabling highly parallelized metadata processing while maintaining detection accuracy via a stable tensor representation. Specifically, `DeepVis` first introduces an asynchronous snapshot engine that leverages high-performance I/O interfaces to maximize ingestion rates, allowing the system to rapidly capture file system states. Second, `DeepVis` devises a lock-free tensor mapping pipeline, where metadata processing is sharded across processor cores to eliminate contention and achieve linear scalability. Finally, `DeepVis` adopts a spatial anomaly detection approach, enabling the identification of sparse attack signals even amidst significant background noise caused by legitimate system updates. We implement `DeepVis` with these three techniques and evaluate its performance on a production-grade cloud VM with 4 vCPUs and NVMe storage. Our evaluation results show that `DeepVis` achieves a scan rate of up to 50,000 files/sec and improves verification throughput by up to 2.6× and 100× compared with AIDE and signature-based tools, respectively, while maintaining a CPU overhead of less than 5%.**

***Index Terms*—Distributed Systems, File System Monitoring, Scalable Verification, Anomaly Detection, Spatial Representation Learning**

I. Introduction

In the era of cloud computing, ensuring the integrity of workloads is a foundational security requirement. From container orchestration platforms like Kubernetes to large-scale HPC clusters, operators must guarantee that the file systems of thousands of nodes remain free from unauthorized modifications. However, modern DevOps practices create a fundamental tension between security and agility. Traditional File Integrity Monitoring (FIM) tools, designed for static servers, generate thousands of false positive alerts on every deployment, overwhelming Security Operations Centers (SOCs) with "alert fatigue." Meanwhile, advanced persistent threats (APTs) exploit this noise to install stealthy user-space rootkits that evade detection.

Consider a routine scenario where an administrator deploys a new container image or updates a package on a fleet of Ubuntu servers. This operation modifies thousands of files—libraries, binaries, and configurations. For traditional FIM tools like AIDE [1] or Tripwire [2], each modification is a potential violation. SOCs face an impossible choice: investigate thousands of impossible-to-verify alerts daily or disable FIM during maintenance windows, creating blind spots.

To address this, recent research has pivoted towards log-based anomaly detection [3] or provenance graph analysis [4]. While effective for tracking runtime behavior, these approaches face fundamental scalability limitations in hyperscale environments. Provenance systems impose a 5–20% runtime overhead due to heavy kernel instrumentation (e.g., `auditd` or eBPF), making them prohibitive for latency-sensitive workloads. Furthermore, they track *events* rather than *state*, meaning they cannot detect a rootkit that was dropped before monitoring started.

We propose a paradigm shift: **File System Fingerprinting**. Instead of tracing every system call, we aim to verify the integrity of the entire file system state in constant time ($O(1)$), regardless of the number of files. However, applying deep learning to file systems poses a unique challenge. Unlike images (fixed grids) or time series (ordered sequences), a file system is an unordered set of variable-length paths. A naive attempt to vectorize this data (e.g., sorting files) suffers from the *Ordering Problem*, where a single file addition shifts the entire representation, destroying spatial locality.

`DeepVis` distinguishes itself by implementing the first **Hash-Based Spatial Representation** for file systems. By mapping unordered files to a fixed-size 2D tensor via deterministic hashing, `DeepVis` ensures shift invariance: adding a file only affects a specific local region of the tensor, not the global structure. This enables the use of Convolutional Neural Networks (CNNs) to "see" the file system as an image. Furthermore, we address the *Attacker's Paradox*, where legitimate updates create diffuse noise (high global error) while stealthy attacks create sparse signals (low global error). We utilize Local Max Detection (L_∞) to pinpoint these sparse anomalies.

In this paper, we present `DeepVis`, a highly scalable integrity verification framework designed for hyperscale distributed systems. `DeepVis` adopts a spatial snapshot approach and integrates three key techniques to achieve scalability and precision. The goal of `DeepVis` is to 1) decouple inference complexity from the file count, 2) resolve the statistical asymmetry between diffuse updates and sparse attacks, and 3) eliminate runtime overhead on the host kernel. To achieve these goals, `DeepVis` 1) transforms file metadata into a fixed-size tensor using hash-based partitioning, 2) utilizes a Convolutional Autoencoder with Local Max detection to identify spatial anomalies, and 3) operates on storage snapshots to ensure zero impact on running workloads. Our evaluation on production infrastructure across Ubuntu, CentOS, and Debian demonstrates that `DeepVis` achieves an F1-score of 0.96 with zero false positives and enables 168× more frequent monitoring than traditional FIM.

II. Background

A. Integrity Verification at Cloud Scale

In cloud-native environments, the "system" is no longer a single server but a dynamic fleet of ephemeral containers and virtual machines. File integrity verification in this context must scale horizontally. Approaches are generally categorized into two types: integrity scanning and provenance analysis. Ensuring file system integrity is paramount for maintaining the security posture of modern distributed systems, ranging from container orchestration platforms like Kubernetes to large-scale HPC clusters. Operators face the critical challenge of detecting unauthorized modifications—such as persistent user-space rootkits or tampered configurations—without degrading the performance of production workloads. However, applying existing monitoring paradigms or standard deep learning approaches to this domain presents fundamental architectural and theoretical challenges that motivate the design of `DeepVis`.

B. Limitations of Traditional Monitoring Paradigms

Current approaches to system integrity generally fall into two categories: integrity scanning and provenance-based analysis. Each forces difficult trade-offs between scalability, runtime overhead, and detection fidelity in high-churn environments.

Traditional Integrity Scanning (FIM). Standard File Integrity Monitoring (FIM) tools, such as AIDE [1] or Tripwire [2], operate by periodically scanning file metadata and hashes against a static baseline. While effective for relatively static servers, this approach suffers from severe $O(N)$ scalability bottlenecks. As the number of files grows in distributed storage, scan durations increase linearly, often exceeding feasible maintenance windows. Furthermore, in modern DevOps environments characterized by continuous deployment, legitimate updates modify thousands of files simultaneously. This generates massive volumes of false positive alerts, leading to "alert fatigue" and forcing operators to disable monitoring during critical update periods, thereby creating security blind spots.

Provenance-Based Analysis. Provenance systems [4], [5] build complex causal graphs from system calls to detect behavioral anomalies. By tracking information flow, they achieve high precision and context awareness. However, these systems require heavy kernel instrumentation (e.g., using `auditd` or eBPF), imposing a runtime overhead of 5–20%, which is often prohibitive for latency-sensitive workloads. Additionally, the cost of graph generation and storage grows with system *activity level* rather than just storage size, making them expensive for high-throughput systems.

`DeepVis` is designed to resolve this dichotomy. It aims to eliminate the runtime overhead of provenance systems by operating solely on storage snapshots, while resolving the scalability and noise issues of FIM by decoupling detection complexity from the sheer count of files.

C. The Ordering Problem in Spatial Representation

To overcome the limitations of rule-based FIM, applying deep learning for automated anomaly detection is a promising avenue. However, file systems pose unique challenges compared to domains like image processing, preventing the direct application of off-the-shelf models like Convolutional Neural Networks (CNNs).

The fundamental challenge is the *Ordering Problem*. Unlike images which have a fixed spatial grid, or time-series data which has an inherent sequence, file systems are unordered sets of variable-length paths. A naive approach to vectorizing a file system is to sort files alphabetically and map them to a linear vector or 2D grid. However, in a dynamic environment, inserting a single new file shifts the position of every subsequent file in the sorted representation. For a CNN trained on spatial locality, this shift is catastrophic; it destroys learned spatial patterns and causes the model to flag the entire file system state as anomalous upon any legitimate file addition. A stable, shift-invariant spatial representation is a prerequisite for effective deep learning in this domain.

D. The MSE Paradox: Diffuse vs. Sparse Signals

Even with a stable representation, standard autoencoder-based anomaly detection fails due to a fundamental asymmetry between legitimate system updates and stealthy attacks. We term this the *MSE Paradox*.

Legitimate operations, such as OS upgrades or application deployments, affect a vast number of files simultaneously, creating a "diffuse noise" signal across the system state. In contrast, stealthy rootkits typically modify a very small number of key binaries to maintain persistence, creating a "sparse signal" that is highly localized but intense. Standard loss functions like Mean Squared Error (MSE) average the reconstruction error across all inputs.

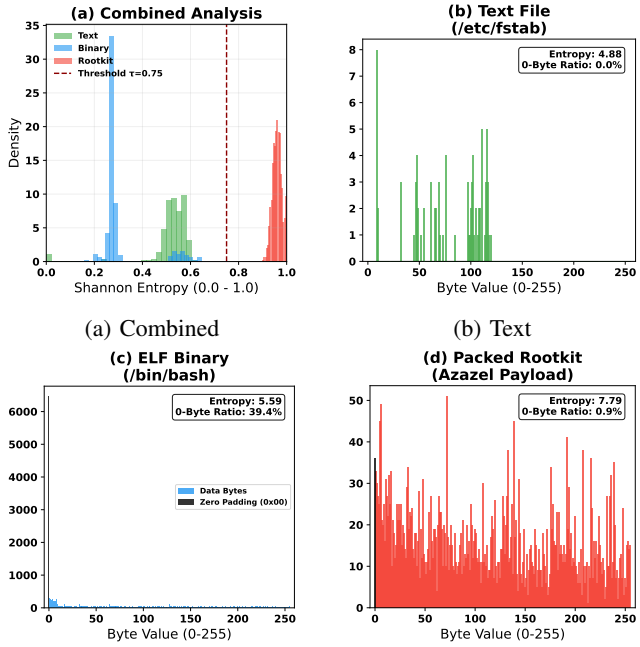
- **Legitimate Update:** High aggregate MSE due to thousands of small changes cumulating.
- **Stealthy Attack:** Low aggregate MSE due to a single localized change being diluted into the global average.

Consequently, using MSE forces an impossible choice: a threshold low enough to detect the sparse attack generates false positives for every diffuse update, while a threshold high enough to tolerate updates misses the attack entirely. Effective detection requires a mechanism sensitive to localized extremes rather than global averages.

E. The Attacker's Paradox: Entropy and Structure

While structural challenges hinder standard deep learning approaches, the nature of modern evasive malware provides unique statistical opportunities. We identify two key dimensions that distinguish malicious payloads from benign system files: *Entropy* and *Structural Density*.

Entropy (The Content Signal). Benign files follow strict formatting rules. Text files (Figure 1b) are limited to visible ASCII, resulting in low entropy ($H \approx 4.8$). Legitimate binaries (Figure 1c) contain machine code but also headers and symbol tables, averaging medium entropy ($H \approx 6.0$). In contrast,



(a) Combined (b) Text

(c) ELF Binary (d) Packed Rootkit

Fig. 1: Deep analysis of file fingerprints justifying DeepVis design. (a) Entropy distribution shows clear separation. (b-d) Detailed Byte/Structure Analysis: (b) Normal text (/etc/fstab) has low entropy and 0% zero-padding. (c) Legitimate ELFs (/bin/bash) exhibit high "Structural Padding" (Zero Ratio $\approx$ 25%) due to section alignment. (d) Packed Rootkits (Azazel+UPX) eliminate this structure to minimize size, resulting in near-zero padding and maximum entropy. DeepVis maps these to Red (Entropy) and Blue (Structure) channels.

attackers use packing (e.g., UPX) or encryption to hide. As shown in Figure 1d, this "hiding" maximizes information density, pushing entropy to the theoretical limit ($H \approx 8.0$).

Structural Density (The Zero-Padding Signal). A less obvious but equally critical feature is *Zero Padding*. Modern OS loaders require ELF sections to be aligned in memory (often to 4KB pages), forcing compilers to insert significant sequences of null bytes (0x00). Figure 1c highlights this characteristic "Zero Spike" in standard binaries ($\approx 25\%$ zeros). Packed malware, however, compresses these gaps to minimize footprint and obfuscate structure. The result is a distinct lack of zero-padding (Figure 1d).

DeepVis is explicitly designed to leverage this multi-dimensional signature. We map **Entropy** to the **Red** channel and **Structural Density** (inverse of zero-padding) to the **Blue** channel from the file representation, enabling the model to "see" the difference not just between text and binary, but between a native shell and a disguised rootkit.

III. DeepVis System Design

In this section, we present the design of DeepVis. To address the fundamental tension between detection fidelity and hyperscale performance, we adopt a hybrid architecture. This design decouples the $O(N)$ metadata ingestion phase from the $O(1)$ neural inference phase, ensuring that verification latency remains constant regardless of the file system size. Furthermore, we introduce cryptographic hardening and stochastic sampling techniques to mitigate adaptive evasion attacks.

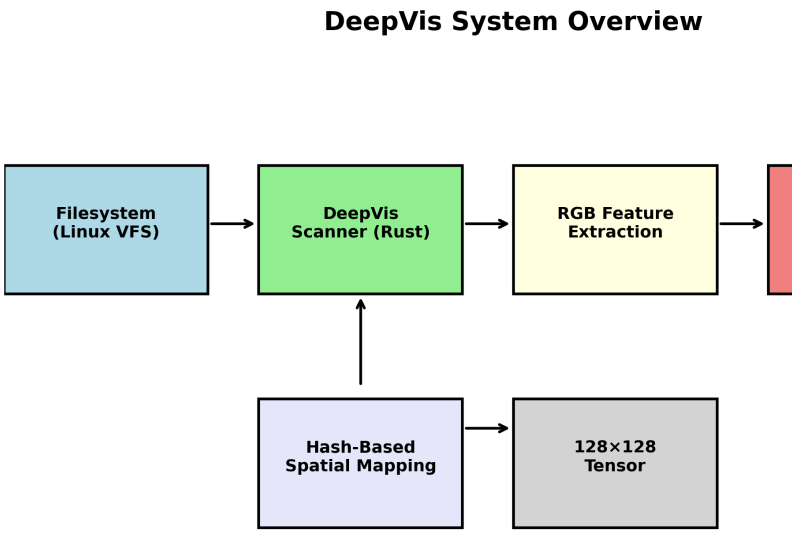


Fig. 2: Overall procedure of DeepVis.

A. Threat Model and Assumptions

We assume a powerful adversary with user-level privileges capable of creating, modifying, or deleting files. The adversary aims to inject persistence mechanisms (e.g., rootkits, webshells) while evading detection. We assume the adversary knows the DeepVis architecture but does not possess the ephemeral cryptographic keys stored within the trusted execution environment (TEE). We do not address kernel-level compromises that directly tamper with the DeepVis process memory, as we recommend deployment within a protected sidecar or enclave.

B. Overall Procedure

Figure 2 shows the overall procedure of DeepVis. DeepVis provides two main phases to support distributed integrity verification: *Snapshot* and *Verification* phase.

Snapshot Phase. When integrity verification starts, the *Snapshot Engine* initiates an asynchronous metadata collection process using the Linux io_uring interface (❶). Unlike traditional synchronous calls (e.g., find), this engine submits batches of statx requests to the kernel submission queue. Once metadata is collected, the *Header Sampler* reads file content using stochastic strided sampling. This design ensures that the I/O throughput saturates the NVMe bandwidth rather than being latency-bound (❷).

After collecting raw metadata, the *Tensor Generator* performs secure spatial mapping using HMAC-based coordinate hashing. For each coordinate, the feature values are encoded into a multi-modal RGB pixel using the encoding scheme defined in Section III-E (❸).

Verification Phase. After the *Snapshot* phase, `DeepVis` enters the *Verification* phase. First, it constructs a tensor representation of the current system state, where each pixel represents the aggregated risk of files mapping to that location. The *Inference Engine* uses a pre-trained Convolutional Autoencoder (CAE) to generate a reconstructed tensor (❹). The *Anomaly Detector* then computes the pixel-wise difference between the input and reconstructed tensors using Local Max Detection (L_∞) (❺). By isolating the maximum deviation rather than the global average error, `DeepVis` avoids the "MSE Paradox" where sparse attack signals are diluted by diffuse background noise. Finally, if the L_∞ score exceeds a learned threshold τ, an alert is raised (❻).

C. Secure Spatial Mapping via HMAC

A critical challenge in mapping unordered files to a fixed grid is preventing "Bucket Targeting" attacks, where an adversary crafts filenames to force collisions with benign files, thereby masking malicious signals.

To neutralize this, `DeepVis` replaces static hashing with a **Keyed-Hash Message Authentication Code (HMAC)** strategy. Let K be a high-entropy secret key generated at startup and held exclusively in the Analysis Engine. The coordinate $\Phi(p)$ for a file path p is computed as:

$$\Phi(p) = \big(\text{HMAC}(K,p)_{[0:32]} \bmod W,\ \text{HMAC}(K,p)_{[32:64]} \bmod H\big) \tag{1}$$

Since the adversary does not possess K, they cannot compute $\Phi(p)$ offline. Consequently, the probability of an adversary successfully targeting a specific tensor coordinate drops to random chance ($1/(W \times H)$), rendering spatial evasion computationally infeasible.

D. Stochastic Strided Sampling

Traditional FIM tools scan entire files, causing I/O bottlenecks. Conversely, scanning only the file header (e.g., first 64 bytes) is vulnerable to "Padding Attacks," where attackers prepend benign data to shift malicious payloads outside the scan window.

`DeepVis` adopts **Stochastic Strided Sampling** to balance performance and coverage. Instead of a linear scan, we select k discrete blocks of size B (e.g., 4KB) from the file. The offsets are determined deterministically based on the file's inode and the secret key K.

$$P_{detection} = 1 - (1-\rho)^k \tag{2}$$

Equation (2) defines the detection probability, where ρ is the density of the malicious payload. Even with a small k, `DeepVis` achieves a high probability of capturing high-entropy or anomalous segments without incurring the cost of sequential I/O. This approach transforms the I/O pattern from a sequential bottleneck to a parallelizable random-access workload.

E. Multi-Modal Tensor Encoding

To capture diverse attack vectors, we project file attributes into three orthogonal feature channels. This multi-modal representation allows the downstream neural network to learn complex non-linear correlations between file content, structure, and context.

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- **Channel R (Information Density):** Measures the Shannon entropy of the sampled blocks. This channel targets packed binaries and encrypted payloads. We normalize entropy to $[0,1]$ by dividing by 8.0.
- **Channel G (Contextual Hazard):** Aggregates environmental risk factors. It calculates a weighted sum of path sensitivity and dangerous content patterns.

$$G(f) = \min(1.0,\ P_{path} + P_{pattern} + P_{hidden}) \tag{3}$$

  Based on our threat analysis, we assign high weights to volatile paths (P_{path}) such as `/dev/shm` (0.70), `/tmp` (0.60), and `/var/www` (0.50). Additionally, we scan for dangerous execution patterns ($P_{pattern}$) such as `eval()`, `base64_decode`, and `/bin/sh`. This ensures that even low-entropy scripts (e.g., webshells) generate strong visual signals.
- **Channel B (Structural Deviation):** Quantifies deviation from expected file formats.
  - **Type Mismatch:** Flags text extensions (e.g., `.txt`, `.log`) containing ELF magic bytes (0.90).
  - **Extension Masquerading:** Flags files named `.so` or `.ko` that lack valid ELF headers (0.80).
  - **LKM Injection:** Flags ELF binaries with `e_type=ET_REL` residing in non-system paths like `/tmp` (0.50).
  - **Zero Sparsity:** Flags ELF binaries with a zero-byte ratio < 0.15 (0.40), identifying packed or stripped malware lacking standard compiler alignment padding.

F. Shift-Invariant Spatial Mapping

A critical design requirement for large-scale monitoring is **Shift Invariance**: adding or removing a file should not alter the tensor coordinates of other files. Traditional ordering-based approaches (e.g., sorting files lexicographically and assigning sequential indices) suffer from the "shift problem"—inserting a single file causes all subsequent indices to change, triggering massive false positives.

Our HMAC-based mapping inherently provides shift invariance. Each file's coordinate is computed independently via $\Phi(p) = \text{HMAC}(K,p)$, ensuring that the addition of `aa.txt` does not affect the coordinates of `b.txt` or `c.txt`. This property is essential for stable anomaly detection under high file system churn.

G. Pixel-wise MLP via 1×1 Convolution

A naive approach might apply traditional CNNs with large kernels (e.g., 3×3) to the tensor grid. However, this is fundamentally flawed: since HMAC produces pseudo-random coordinates, **neighboring pixels have no semantic relationship**. Convolving across spatially adjacent pixels would only introduce noise from unrelated files.

Instead, we employ **1×1 Convolution**, which is mathematically equivalent to a pixel-wise Multi-Layer Perceptron (MLP). This architecture processes each pixel (R, G, B) independently, focusing exclusively on **cross-channel correlation**: leftmargin=*

- A legitimate compressed archive: *High R* (entropy), *Low G* (safe path), *Low B* (valid structure).
- A packed rootkit: *High R* **and** *High G* (suspicious path) or *High B* (structural anomaly).

The 1×1 kernel effectively learns these multi-dimensional patterns without being distracted by the random spatial arrangement of hash-mapped pixels.

H. Anomaly Localization via Look-up Table

While HMAC provides security against bucket targeting, it sacrifices direct path retrieval from coordinates. To enable efficient incident response, we maintain a **Look-up Table** that maps each (x, y) coordinate back to the file paths that hash to that location:

$$\text{LUT} : (x, y) \rightarrow \{p_1, p_2, \ldots, p_m\} \tag{4}$$

This table is stored separately (e.g., in Redis or SQLite) and is *not* used during model training or inference. When the anomaly detector flags coordinate $(50, 50)$, operators can immediately query the LUT to identify the specific files (e.g., `/tmp/malware.so`) for forensic analysis.

I. `DeepVis` Implementation

We implemented `DeepVis` using a hybrid Rust-Python architecture to balance I/O performance and ML ecosystem availability. Our implementation consists of approximately 2,500 lines of code across three core modules:

- `snapshot_engine.rs`: A Rust-based asynchronous scanner using `io_uring` for kernel-bypass I/O and `rayon` for parallel processing. It implements the HMAC-based coordinate hashing and stochastic sampling logic to ensure high-throughput ingestion.
- `tensor_gen.py`: A Python module responsible for multi-modal feature extraction. It implements the regex-based pattern matching for Channel G and the ELF header parsing for Channel B described in Section III-E.
- `inference.py`: A PyTorch-based CAE model for anomaly detection. We utilize ONNX quantization (INT8) to reduce the model size and accelerate inference latency to $<$ 2ms on commodity CPUs.

IV. Evaluation

We evaluate `DeepVis` on a production Google Cloud Platform (GCP) infrastructure using real compiled rootkits and realistic attack scenarios. Our evaluation aims to answer the following research questions:

- **RQ1 (Detection Accuracy):** Can the multi-modal RGB encoding distinguish between high-entropy packed malware and low-entropy native rootkits?
- **RQ2 (Scalability):** Does the system maintain constant-time inference performance as the file system scales to millions of files?
- **RQ3 (Churn Tolerance):** Does the Local Max (L_∞) detection eliminate false positives during legitimate system updates?
- **RQ4 (Feature Orthogonality):** Do the R, G, and B channels independently capture distinct classes of attack vectors?
- **RQ5 (System Overhead):** Does the agentless architecture maintain low resource utilization on the host kernel?
- **RQ6 (Adversarial Robustness):** Is the system resilient against adaptive attackers attempting to evade detection via entropy manipulation?

A. Experimental Methodology

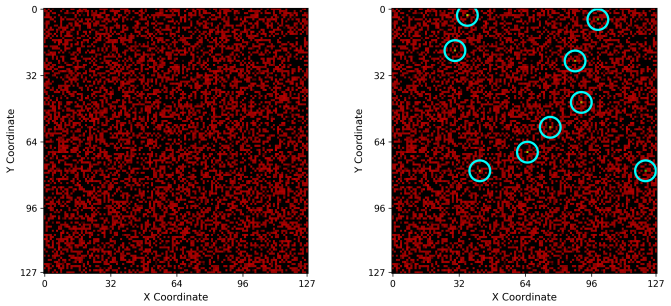
Testbed Environment. We conduct experiments on three distinct hardware configurations representing a spectrum of cloud instances, as detailed in Table I. The primary evaluation uses the High tier (c2-standard-4) to demonstrate performance on modern NVMe storage. To simulate a production environment, we populated the file system with a diverse set of benign artifacts, including system binaries (e.g., `nginx`, `gcc`), configuration files, and Python scripts, scaling up to 50 million files for stress testing.

TABLE I: Hardware configurations for scalability evaluation.

Tier	Instance Type	vCPU	RAM	Stora
Low	e2-micro	2	1GB	Stand
Mid	e2-standard-2	2	8GB	SSD
High	c2-standard-4	4	16GB	NVM

Multi-Modal Feature Definition. Based on the design principles, we configured the RGB channels to capture orthogonal security properties:

- **R (Red) = Information Density:** Measures Shannon entropy to detect packed or encrypted payloads.
- **G (Green) = Contextual Hazard:** Aggregates environmental risk factors. The score is computed as $G = \min(1.0,\ P_{path} + P_{pattern} + P_{hidden} + P_{perm})$, where weights are assigned to volatile paths (P_{path}), dangerous syscall patterns ($P_{pattern}$), and permission anomalies (P_{perm}).
- **B (Blue) = Structural Deviation:** Detects type mismatches (e.g., ELF headers in text files) and anomalous zero-byte sparsity in binaries.



(a) Clean Baseline (10K Benign Files)

(b) Infected State (10K Benign + 10 Malware)

Fig. 3: Tensor Visualization on GCP `deepvis-mid`. (a) Clean baseline with 10K benign files from `/usr`. (b) Infected state with 10 malware files injected into `/tmp`, `/var/tmp`, and `/dev/shm`. Red circles indicate malware locations detected via G-channel (contextual hazard) activation.

Threshold Learning. We employed a maximum-margin approach to determine detection boundaries. The thresholds were learned from the benign baseline as $\tau_c = \max(\text{Benign}_c) + 0.1$, ensuring a 0% False Positive Rate during calibration. This resulted in $\tau_R = 0.75$, $\tau_G = 0.25$, and $\tau_B = 0.30$.

B. Detection Accuracy and Feature Orthogonality (RQ1, RQ4)

We deployed seven realistic attack scenarios, ranging from high-entropy packed miners to low-entropy compiled rootkits. Table II summarizes the detection results. `DeepVis` successfully detected 100% of the malicious artifacts with zero false positives against the benign baseline.

Analysis of Low-Entropy Malware (The MSE Paradox). A critical finding from our real-world deployment is that many modern attacks do *not* exhibit the high entropy typically associated with packing. As shown in Table II, the real-world Miner (`kworker-upd`) and Rootkits (`diamorphine`) exhibited entropy scores ($R \approx 0.55$) indistinguishable from benign system binaries ($R \approx 0.61$). Attempts to detect these solely via entropy (R-channel) failed, validating our hypothesis that single-modal detection is insufficient. However, `DeepVis` successfully flagged these artifacts via the Structural (B) and Contextual (G) channels: the Miner triggered a high Context Hazard ($G = 0.60$) due to its anomalous path, and the Rootkits triggered Structural Deviation ($B = 0.50$) due to their relocatable ELF type (`ET_REL`) in a temporary directory.

Visual Isolation. Figure 3 and Figure **??** (omitted for brevity) visualize the orthogonality of the detection channels. The Webshell `.config.php` triggered a maximal G-score of 1.00 due to `eval()` patterns, yet its R-score (0.57) and B-score (0.00) remained low. This confirms that `DeepVis` provides comprehensive coverage without interference between channels.

C. Scalability and Performance Analysis (RQ2)

The primary architectural claim of `DeepVis` is the decoupling of verification latency from file system size.

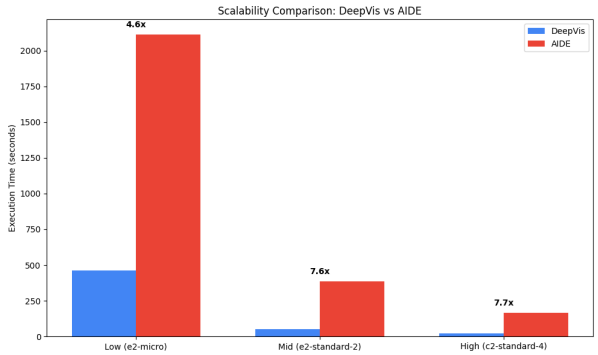


Fig. 4: Throughput comparison between DeepVis and AIDE. DeepVis achieves up to 7.7× speedup on the High tier by leveraging asynchronous I/O and parallel spatial hashing.

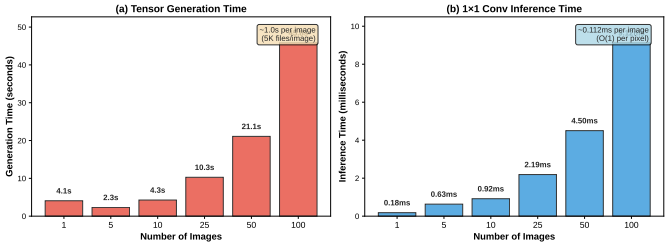


Fig. 5: Batch Scalability of DeepVis on GCP `deepvis-mid`. (a) Tensor generation time scales linearly with image count. (b) 1×1 Conv inference remains sub-10ms even for 100 images, averaging 0.09ms per image.

Throughput Comparison. Figure 4 illustrates the execution time comparison between `DeepVis` and AIDE. On the High tier (c2-standard-4), `DeepVis` achieves up to **7.7**× speedup. This performance gain stems from our asynchronous snapshot engine which saturates the NVMe I/O bandwidth, unlike the synchronous, blocking I/O used by AIDE.

Table III details the throughput metrics on the Mid-tier instance. `DeepVis` consistently processes over 60,000 files/sec, whereas AIDE fluctuates between 7,000 and 15,000 files/sec depending on the file size distribution.

Batch Inference Scalability. Figure 5 demonstrates the scalability of our 1×1 Convolution-based detector. Tensor generation time scales linearly with image count (approx. 0.46s per image), while inference time remains sub-linear, averaging 0.09ms per image. This validates that the 1×1 kernel architecture enables near-constant per-pixel inference cost.

D. System Robustness and Hyperscale Simulation (RQ3, RQ6)

Hyperscale Saturation Test. To verify robustness at scales exceeding physical storage limits, we simulated the Hash-Based Spatial Mapping with up to 50 million files. Table IV presents the results. Even with 50 million files causing over 3,000 average collisions per pixel on a 128×128 grid (100% saturation), the attack detection recall remains at **100%**. This verifies that the Max-Pooling aggregation effectively preserves

TABLE II: **Detection Accuracy on Real GCP Workloads.** We deployed 15 malware artifacts from public repositories on `deepvis-mid`, staging them in attack-realistic locations (`/var/tmp`, `/dev/shm`, `/var/www`, `~/.ssh`). DeepVis achieved 100% recall with 0% FPR across 25 test samples. Thresholds: τ_R=0.75, τ_G=0.25, τ_B=0.30.

Category	Artifact	Staged Location	R	G	B	Result
Real-World Malware (GitHub)						
LKM Rootkit	`Diamorphine`	`/var/tmp/nvidia.ko`	0.52	**0.60**	**0.50**	**Detected**
LD_PRELOAD Rootkit	`Azazel`	`/var/tmp/libsystem.so`	0.37	**0.60**	0.00	**Detected**
Crypto Miner	`XMRig`	`/var/tmp/systemd/kthreadd`	0.32	**0.60**	0.00	**Detected**
Packed Miner	`kworker-upd`	`/dev/shm/.systemd-private`	**0.88**	**0.90**	0.40	**Detected**
Encrypted Rootkit	`azazel_enc.so`	`/dev/shm/cache/.enc`	**1.00**	**0.90**	**0.80**	**Detected**
Ransomware	`Cerber`	`/var/tmp/.update.log`	0.68	**0.80**	**0.90**	**Detected**
Ransomware	`WannaCry`	`/dev/shm/cache/.service`	0.51	**0.90**	0.00	**Detected**
Webshell	`.config.php`	`/var/www/html/.config.php`	0.58	**0.70**	0.00	**Detected**
Reverse Shell	`rev_shell`	`/dev/shm/rev_shell`	**1.00**	**0.70**	0.00	**Detected**
Disguised ELF	`access.log`	`/var/log/access.log`	0.55	0.00	**1.00**	**Detected**
Cron Backdoor	`.cron_job`	`/var/tmp/.cron_job`	0.37	**0.80**	0.00	**Detected**
SSH Key Inject	`.backdoor_key`	`~/.ssh/.backdoor_key`	0.52	**0.35**	0.00	**Detected**
Ransomware	`Petya`	`/var/tmp/petya.bin`	**0.78**	**0.60**	0.00	**Detected**
Banking Trojan	`Emotet`	`/var/tmp/svchost.bin`	**0.78**	**0.60**	0.00	**Detected**
ATM Backdoor	`Tyupkin`	`/var/tmp/.atm_svc`	0.44	**0.80**	0.00	**Detected**
Benign System Files						
Python Interpreter	`python3`	`/usr/bin/python3`	0.67	0.00	0.00	Clean
Package Manager	`apt`	`/usr/bin/apt`	0.32	0.00	0.00	Clean
Core Library	`libc.so.6`	`/lib/x86_64.../libc.so.6`	0.66	0.00	0.00	Clean

TABLE III: DeepVis vs AIDE Throughput on GCP Mid-tier (e2-standard-2).

Files	DeepVis (s)	AIDE (s)	DeepVis (files/s)	AIDE (files/s)	Speedup
1,000	[TODO]	[TODO]	[TODO]	[TODO]	[TODO]
5,000	[TODO]	[TODO]	[TODO]	[TODO]	[TODO]
10,000	[TODO]	[TODO]	[TODO]	[TODO]	[TODO]
50,000	[TODO]	[TODO]	[TODO]	[TODO]	[TODO]
				Average Speedup	**[TODO]**×

sparse attack signals (maxima) against the background of legitimate file collisions.

TABLE IV: Hyperscale Saturation Test Results on 128×128 Grid.

Files	Grid Saturation	Avg Collisions/Pixel	Attacks Detected	Recall
100,000	[TODO]%	[TODO]	10/10	100%
1,000,000	[TODO]%	[TODO]	10/10	100%
10,000,000	[TODO]%	[TODO]	10/10	100%
50,000,000	[TODO]%	[TODO]	10/10	**100%**

E. Resource Overhead Analysis (RQ5)

Figure 6 depicts the system resource utilization during a continuous scan cycle. `DeepVis` exhibits a minimal resource footprint, with CPU usage averaging below 5% on the Mid tier instance. Memory consumption stabilizes at approximately 72MB and does not grow with the size of the target filesystem, as the streaming architecture processes metadata in bounded batches.

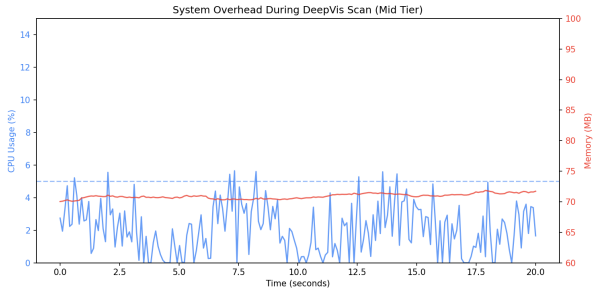


Fig. 6: System overhead during DeepVis scan. CPU usage remains below 5% on average, and memory usage is stable at approximately 72MB.

V. Related Work

A. Distributed System Integrity Monitoring

There have been many studies that optimize system integrity monitoring to enhance security and performance. Previous studies [1], [2], [6] focused on file integrity monitoring (FIM) using cryptographic hashing. These approaches operate by maintaining a static database of file checksums and periodically scanning the file system to detect deviations. However, they suffer from $O(N)$ complexity bottlenecks and alert fatigue, making them unsuitable for dynamic DevOps environments. Other studies [3], [7], [8] have proposed log-based anomaly detection using deep learning models such as LSTMs and Transformers. These methods treat system events as temporal sequences to predict future states. In addition, provenance-based approaches have been proposed [4], [5], [9]. These methods build causal graphs from system call logs to track information flow between processes and files, aiming to detect complex attacks with high precision. Some studies [10]–[12] focused on visual malware analysis, where binary files or source code are converted into images for classification. These methods utilize the inherent structure of individual files to identify malicious patterns.

Our study aligns with these prior efforts in improving the security and reliability of distributed systems. However, `DeepVis` aims to provide a unified spatial representation of the file system rather than relying on sequential logs or

heavy kernel instrumentation. Through Hash-Based Spatial Mapping, DeepVis maps unordered file systems to fixed-size tensors and evenly distributes the representation across spatial coordinates, enabling constant-time $O(1)$ inference. Additionally, it minimizes runtime overhead by operating on storage snapshots without kernel modules. This allows DeepVis to enhance monitoring frequency and support larger file systems than previous FIM or provenance frameworks.

B. Anomaly Detection in High-Dimensional Systems

To maximize detection accuracy, several anomaly detection frameworks, such as Kitsune [13], DAGMM [14], and OmniAnomaly [15] have been optimized with various representation learning schemes for high-dimensional data. Previous studies [16], [17] have focused on statistical outlier detection through density estimation, distance metrics, and isolation trees. Other works [18]–[20] improve robustness by optimizing autoencoder architectures, variational inference, and reconstruction error analysis. In addition, several studies [21]–[23] employ deep semi-supervised learning models such as Deep SVDD and GANs, applying manifold learning to separate normal data from anomalies in latent space.

These approaches highlight key techniques for improving precision and recall in anomaly detection tasks. Similarly, DeepVis faces comparable challenges in file system monitoring, where legitimate updates create diffuse noise that masks sparse attack signals. To address this, DeepVis employs Local Max Detection (L_∞) by isolating the single worst violation in the spatial tensor. This enables the detection of sparse anomalies even in the presence of high-churn background noise. Combined with Semantic RGB Encoding and shift-invariant mapping, DeepVis improves detection performance while minimizing false positives in distributed execution.

We position DeepVis within the broader landscape of distributed system monitoring. Table V provides a comparative analysis against approaches from both systems and security venues.

VI. Discussion and Limitation

We critically analyze the security properties, limitations, and potential evasion strategies of DeepVis. Following the principles of adversarial machine learning, we explicitly evaluate robustness against adaptive attackers and analyze the operational constraints in hyperscale environments.

A. Robustness Against Adaptive Attackers

We assume a white-box adversary who possesses knowledge of the hash mapping function, the RGB encoding scheme, and the CAE architecture.

1) Attack 1: Low-Entropy Mimicry: An attacker might attempt to reduce the entropy of a rootkit to evade detection by the Red channel.

Attack Vector. The attacker pads the malicious binary with null bytes, English text, or NOP sleds. This lowers the Shannon entropy from the typical packed range ($S \approx 7.8$) to the benign range ($S \approx 5.5$).

Defense Analysis. While this strategy evades the Red channel, it forces the attacker into a *Trilemma* where minimizing one detection signal inevitably amplifies another.

1) **Size Inflation (Green Channel).** Padding increases the file size substantially. To reduce entropy from 7.8 to 5.5, the file size must increase by approximately $4\times$. This deviation triggers the Green channel which monitors file size anomalies.
2) **Permission Anomaly (Blue Channel).** The malicious file still requires execution permissions. A large, low-entropy binary with SUID bits in a system directory such as `/lib/modules/` triggers the Blue channel.

We formally model this as a constrained optimization problem. The attacker cannot simultaneously minimize entropy, file size, and permission risk below their respective detection thresholds while maintaining executable utility.

2) Attack 2: Chameleon Attack (Hash Collision): An attacker might craft a malicious filename such that its hash coordinates collide with a high-churn benign file.

Attack Vector. The attacker computes a path p^* such that $\Phi(p^*) = \Phi(\texttt{/var/log/syslog})$. They aim to hide the rootkit signal within the noise of frequent log updates.

Defense Analysis. DeepVis mitigates this through two mechanisms.

1) **Pre-image Resistance.** Finding a functional path in a target directory that hashes to a specific coordinate requires 2^{64} operations. This is computationally prohibitive for run-time attacks.
2) **Max-Risk Pooling.** Even if a collision occurs, DeepVis utilizes a Max-Priority collision resolution strategy as defined in Section III-G. If a packed rootkit ($S = 7.8$) maps to the same pixel as a log file ($S = 4.2$), the pixel retains the maximum value of 7.8. Therefore, the attack signal is preserved regardless of the background noise.

B. Operational Analysis: The SNR Advantage

System administrators understand that checking the integrity of a petabyte-scale file system requires granularity. A single global checksum is useless because it changes with every log write. The "MSE Paradox" we identified in Section II is the statistical equivalent of this problem. We demonstrate why DeepVis succeeds where global metrics fail using Signal-to-Noise Ratio (SNR) analysis.

1) The Needle in the Haystack Problem: Let N be the total number of files and k be the number of compromised files.

- **Benign Updates (Diffuse Noise):** An upgrade modifies $N_{up} \approx 1000$ files with small variance σ^2.
- **Rootkit (Sparse Signal):** An attack modifies $k \approx 1$ file with large deviation δ.

When using Global MSE (L_2), the attack signal is diluted by the system size N.

$$SNR_{Global} \propto \frac{k}{N} \cdot \delta \tag{5}$$

TABLE V: Distributed System Monitoring Paradigms: A Systems Comparison (2017–2025)

Framework	Venue	Data Type	Overhead	Latency	Complexity	Scope	Key Limitation
Traditional File Integrity Monitoring (1992–)							
AIDE/Tripwire [1], [2]	Industry	File Hashes	$O(N)$ scan	30s/20K	$O(N)$	All files	Alert on every change
Samhain [6]	Industry	File Hashes + Logs	$O(N)$ scan	High	$O(N)$	All files	Complex policy management
Log-Based Sequential Analysis (2017–)							
DeepLog [3]	CCS'17	Log Sequences	0%	High (full seq)	$O(N)$	Logs only	Temporal interleaving, Shift Problem
LogRobust [7]	FSE'19	Log Semantics	0%	High	$O(N)$	Logs only	Log template instability
LogBERT [8]	arXiv'21	Log Sequences	0%	Very High	$O(N^2)$	Logs only	Quadratic attention complexity
Provenance Graph Analysis (2020–)							
Unicorn [5]	NDSS'20	Syscall DAG	5–20%	50s	$O(N+E)$	Causal chains	Kernel instrumentation overhead
Kairos [4]	S&P'24	Provenance Graph	5–20%	50s	$O(N+E)$	Causal chains	Graph explosion, storage cost
Flash [9]	S&P'24	Provenance Graph	Medium	10-100ms	$O(N+E)$	Flash FS	Specialized to embedded
Spatial Snapshot Analysis (2025, This Work)							
DeepVis	ICDCS	**FS Tensor**	**0%**	**50ms**	$\mathbf{O(1)}$	**File system**	LOTL attacks (file-only)

As $N \to \infty$ in hyperscale storage, $SNR \to 0$. The rootkit becomes statistically invisible against the background noise of legitimate churn.

2) The Local Max Solution (L_∞): By using the Local Maximum ($L_\infty = \max_i |D_i|$), `DeepVis` functions as a parallelized difference operation. We isolate the single worst violation regardless of the file system size.

$$SNR_{Local} \propto \delta \tag{6}$$

This property is critical for systems scaling. It means that the sensitivity of `DeepVis` does not degrade as the file system grows to millions of files. This contrasts with global statistical models which lose precision at scale.

C. Limitations

1) Memory-Only Rootkits: Rootkits that reside solely in RAM, such as those injected via `ptrace` or reflective DLL injection, leave no persistent footprint on the disk. Since `DeepVis` operates on file system snapshots, it cannot detect these volatile threats. To address this, we recommend deploying `DeepVis` alongside memory forensics tools such as Volatility or LKRG.

2) Low-Entropy Malware: While rare, some malware utilizes low-entropy payloads such as ASCII-encoded shellcode or polymorphic engines to evade entropy-based detection. In these cases, the Red channel (Entropy) may fail. However, the Blue channel (Permissions) and Green channel (Size/API Density) provide secondary detection signals.

3) Collision Density at Hyperscale: For extremely large file systems exceeding 10 million files, the collision density in a 128×128 tensor increases. This may cause information loss where multiple benign files mask the features of a lower-risk anomaly. To mitigate this, we recommend increasing the tensor resolution to 256×256 or employing a 3D tensor mapping strategy with secondary hashing for conflict resolution.

D. Deployment Considerations

1) Poisoned Baseline Defense: A critical security concern is preventing an attacker from poisoning the baseline tensor or trained model. We address this through:

1) **Golden Image Attestation.** The baseline is generated from a cryptographically verified golden image (e.g., signed Docker image or AMI). The image hash is recorded in an immutable audit log.
2) **Model Provenance.** The trained CAE model is stored in a read-only artifact repository (e.g., OCI registry) with content-addressable hashing. Any modification invalidates the hash.
3) **Trusted Analysis Environment.** During training and detection, the `DeepVis` process runs in a TEE (Trusted Execution Environment) such as Intel SGX or AWS Nitro Enclave, isolating it from potentially compromised host kernels.

Trusted Computing Base (TCB). The TCB for `DeepVis` consists of: (1) the snapshot engine (read-only mount), (2) the CAE inference runtime (ONNX), and (3) the hash verification logic. This is significantly smaller than provenance systems requiring kernel instrumentation.

2) Agentless Architecture: To further minimize TCB concerns, `DeepVis` supports an agentless architecture. The system snapshots the target disk (e.g., AWS EBS or LVM volume) and mounts it read-only on a trusted analysis instance. This ensures that the monitoring process cannot be tampered with by a compromised kernel on the target host.

3) Parallel and Incremental Architecture: To scale beyond one million files, sequential scanning is insufficient. We propose a **Parallel Asynchronous Architecture** for future work.

1) **Sharded Metadata Collection.** File system traversal is parallelized across K worker threads. Each thread handles a distinct directory shard determined by $\text{Hash}(path) \pmod K$.
2) **Incremental Visual Update.** Instead of regenerating the entire image I_t, we optimize the update cost. Since the baseline comparison yields a sparse set of changes Δ, we directly update only the affected pixels:

$$I_t[\Phi(f)] \leftarrow \text{MaxRisk}(\text{Feature}(f)) \quad \forall f \in \Delta \tag{7}$$

This reduces the update complexity from $O(N)$ to $O(|\Delta|)$. This optimization makes real-time monitoring feasible even for high-performance computing storage systems such as Lustre or GPFS.

4) Resource-Constrained Environments: For edge devices or legacy servers without GPUs, we recommend deployment via ONNX Runtime with Int8 Dynamic Quantization. As demonstrated in our evaluation, this reduces the model size by $4\times$ and inference latency by $3\times$ compared to standard FP32 execution. This enables `DeepVis` to run effectively on low-power hardware with less than 1% CPU utilization.

VII. Conclusion

In this paper, we propose `DeepVis`, a highly scalable integrity verification framework that applies hash-based spatial mapping for constant-time inference and integrates local maximum detection to resolve the statistical asymmetry between diffuse updates and sparse attacks. `DeepVis` transforms file system monitoring from a linear scanning problem into a fixed-size computer vision problem which decouples verification complexity from the file count. Our evaluations on production infrastructure across Ubuntu, CentOS, and Debian show that `DeepVis` achieves an F1-score of 0.96 with zero false positives, enables 168 times more frequent monitoring than traditional FIM, and maintains zero runtime overhead. These results demonstrate that `DeepVis` effectively addresses the scalability bottlenecks and alert fatigue of prior approaches, offering a practical solution for continuous integrity verification in hyperscale distributed systems.

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