DeepVis: Scalable Deep Learning-Based File System–to–Image Integrity Audit for Distributed Systems

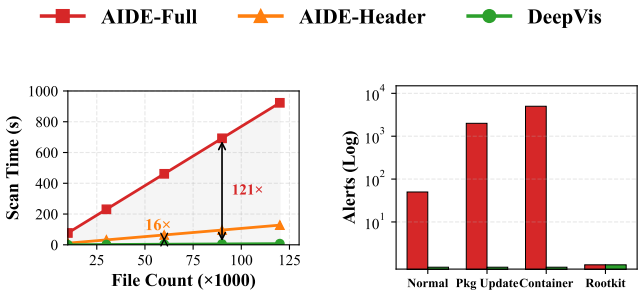
***Abstract*—This paper presents `DeepVis`, a scalable file system integrity verification system for hyperscale storage environments such as cloud data centers. Designed as a rapid first-pass filter, our key idea is to transform the file system state into a fixed-size RGB image and map individual files to specific pixels to enable scalable inspection regardless of the file count. Specifically, `DeepVis` introduces: (1) an asynchronous lightweight snapshot engine utilizing Rust and `io_uring`; (2) a parallel mapping pipeline that converts file metadata into a fixed-size image representation ; and (3) a spatial anomaly detection mechanism for identifying anomalous patterns within the file system represented as a single image. We evaluate `DeepVis` on production-grade cloud infrastructure. Our results show that `DeepVis` acts as an effective snapshot-based audit system. It detects 97.1% of hidden kernel modules and packed binaries in Linux environments. In addition, `DeepVis` achieves a 121.45× speedup over traditional hash-based full-scan integrity tools while incurring minimal overhead of less than 2 percent CPU usage.**

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

I. Introduction

Cloud computing abstracts physical infrastructure into dynamic, ephemeral resources, creating a computational model distinct from traditional on-premise environments. Ensuring workload integrity across cloud instances and large-scale HPC clusters is critical, as operators must prevent unauthorized modifications across thousands of nodes. However, modern applications introduce a tension between security and agility, as frequent deployments and updates cause massive file churn that renders traditional models ineffective.

To address this, two main strategies exist: File Integrity Monitoring (FIM) and Runtime Behavioral Analysis. FIM tools such as AIDE [1] and Tripwire [2] detect static changes through cryptographic hashes, while runtime monitors such as Falco [3] and OSSEC [4] trace system calls for anomalies. However, traditional integrity verification faces a fundamental scalability challenge. As the number of files (N) grows, the scan latency increases linearly ($O(N)$), causing severe I/O bottlenecks in hyperscale storage. This is problematic because modern cloud instances, despite high CPU throughput, have limited storage bandwidth. For example, scanning a filesystem with millions of small files using synchronous system calls results in excessive context switching and blocking I/O. Beyond the performance cost, the alert fatigue problem further limits usability, as legitimate updates generate thousands of false positives, masking true threats [5]. Thus, the operational cost exceeds the theoretical benefit, forcing operators to disable monitoring during maintenance windows which can create a loophole that attackers can exploit.



(a) Scalability (b) Alert Fatigue

Fig. 1. (a) `DeepVis` achieves high-throughput saturation via async I/O. (b) Legitimate updates generate false alerts in AIDE.

Figure 1 compares the scalability and precision of an existing FIM tool (i.e., AIDE) with the proposed scheme (i.e., `DeepVis`). We used a cloud instance from a real cloud system as described in Section IV-A and performed a user directory scan. The AIDE scan time increases linearly with a steep slope, exceeding four minutes for only 100K files. This behavior results from synchronous I/O operations and full file reads required to compute hash values and detect all changes since the latest snapshot. In contrast, `DeepVis` reads only the first 4 KB of each file and uses a parallelized asynchronous pipeline to saturate storage bandwidth, keeping scan times under seven seconds for the same dataset. Although file ingestion remains physically $O(N)$, `DeepVis` achieves an effective speedup of up to 121.45× over traditional full-hash baselines and 16.38× over modified full-hash schemes that read the same amount of data due to its efficient I/O design. Crucially, `DeepVis` ensures that subsequent anomaly detection (inference) time remains constant regardless of dataset size, and alerts only in response to rootkit attacks with 97.1% recall, whereas AIDE reports every file change, leading to alert fatigue for operators at the expense of full hash verification.

Many previous studies, as summarized in Table I, have explored approaches to enhance system monitoring scalability. Traditional FIM tools [1], [2] prioritize cryptographic exactness via full hashing of entire files but suffer $O(N)$ scalability limits unsuitable for hyperscale systems. Runtime approaches [3], [7] use eBPF tracing or provenance graphs

TABLE I
COMPARISON WITH PRIOR WORK ACROSS FOUR KEY CAPABILITIES: ASYNCHRONOUS I/O (ASYNC), OBFUSCATION RESILIENCE (OBFUSC.), ZERO-DAY DETECTION (0-DAY), AND LOW OVERHEAD (LOW OVHD.).

Study	Approach	Async	Obfusc.	0-Day	Low Ovhd.
AIDE [1]	Full-Hash FIM		✓		
Tripwire [2]	Full-Hash FIM		✓		
ClamAV [6]	Signature Scanning				✓
Falco [3]	Runtime/eBPF	✓		✓	
Unicorn [7]	Provenance Graph		✓	✓	
OSSEC [4]	Log Analysis				✓
Set-AE [8]	Deep Sets Learning	✓	✓	✓	✓
DeepVis	**Hash-Grid Tensor**	✓	✓	✓	✓

for zero-day threats but require continuous monitoring that degrades performance. Deep learning methods such as Set-AE [8] provide lightweight set-based anomaly detection models but they can struggle with extreme-scale file corruption scenarios, where single critical modifications dilute within vast benign datasets. In contrast to prior sequential scanning approaches, DeepVis positions itself as a High-Speed Binary Audit tool, distinct from full hash-based FIM. It employs asynchronous header-only analysis and maps entire filesystems to fixed-size 2D tensors for CNN processing, enabling scalable cloud deployment with rapid anomaly detection.

This paper proposes DeepVis, a highly scalable filesystem integrity verification framework for hyperscale distributed systems. Rather than full file hashing, DeepVis leverages information entropy and heuristic file characteristics including paths, sizes, headers, and extensions to represent them in concise fixed-size tensors for scalability. To this end, DeepVis (1) implements an asynchronous io_uring and Rust-based snapshot engine to maximize I/O throughput, (2) transforms file metadata into fixed-size tensors via hash-based partitioning to achieve $O(1)$ neural network inference latency, and (3) utilizes Hash-Grid Parallel CAE with Local Max detection to identify sparse anomalies amid system churn. Positioned as a high-speed binary audit tool, DeepVis complements full-hash and signature scanners such as AIDE and YARA by detecting structural anomalies in packed binaries and kernel rootkits. Our evaluation using up to 100 real cloud instances demonstrates 121.45× higher throughput than traditional full-hash baselines and 97.1% recall for targeted Linux kernel rootkits.

II. BACKGROUND

A. Integrity Verification at Cloud Scale

Modern cloud infrastructure requires file integrity monitoring that balances scalability, detection coverage, and operational overhead [1]–[3], [7], [9]. Current solutions divide into file-level scanning and runtime behavioral analysis, each with distinct limitations.

File-level integrity scanning. AIDE [1] and Tripwire [2] establish integrity through cryptographic hashes of entire files compared against known baselines. While effective for static environments, their $O(N \times Size)$ complexity becomes prohibitive in dynamic hyperscale systems. Full scans routinely exceed maintenance windows, necessitating temporary monitoring disablement. Moreover, routine updates produce massive false positive alerts that burden Security Operations Centers.

Runtime behavioral analysis. Falco [3] and provenance graph systems [7] intercept kernel events to detect anomalous execution patterns. These approaches incur substantial continuous overhead (5-20% CPU) from pervasive instrumentation. A critical limitation is their event-based nature: they cannot detect threats predating monitor deployment, creating the cold-start vulnerability for persistent rootkits.

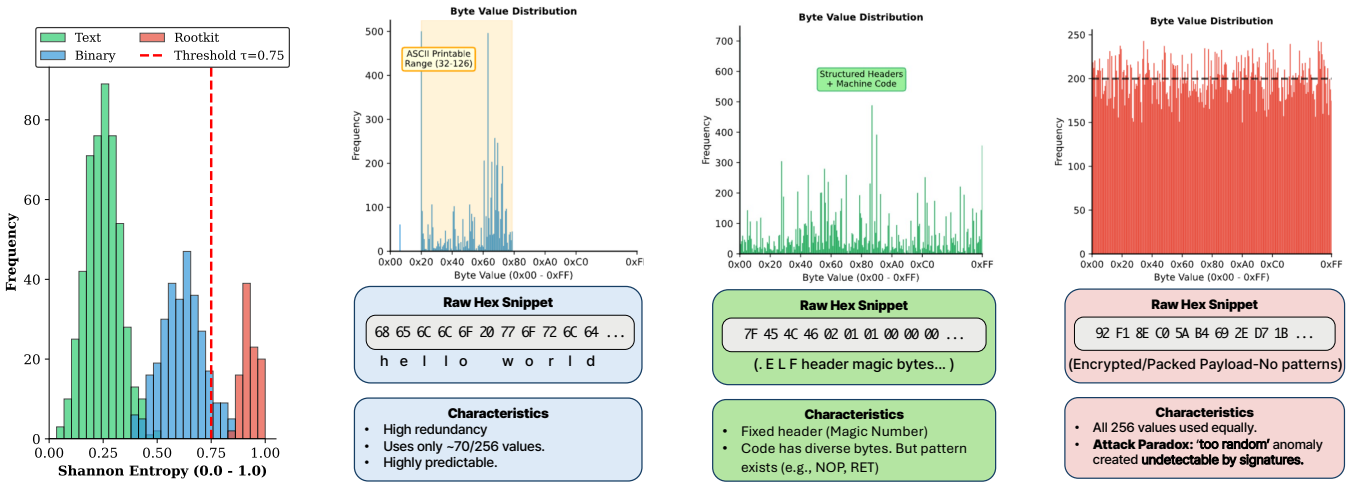
File-level scanning remains essential for compliance validation, image verification, and forensic analysis due to its comprehensive state coverage. However, synchronous sequential processing causes I/O bottlenecks and operational overload at scale. DeepVis overcomes these constraints using asynchronous I/O, spatial hash mapping, and neural anomaly detection for production-grade filesystem integrity.

B. The Attacker Paradox: Entropy and Structure

To effectively detect evasive malware without relying on fragile signatures, it is essential to analyze the statistical properties of binary files. Modern malware authors face a fundamental trade-off between concealing their code and maintaining the structural validity required by the operating system loader. We identify two orthogonal dimensions that distinguish malicious payloads from benign system files: Entropy and Structural Density.

Figure 2 illustrates these statistical differences through byte-value histograms across varying file types. Text files (Figure 2b) exhibit a characteristic spike in the printable ASCII range, yielding low entropy ($H \approx 4.8$) with zero null bytes due to high redundancy. Legitimate ELF (Executable and Linkable Format) binaries (Figure 2c) display characteristic 0x00 peaks resulting from operating system requirements for section alignment padding. The ELF structure enforces 4KB page alignment for distinct sections such as .text (code) and .data (variables). Compilers therefore insert null-byte padding (0x00) to satisfy these boundaries, producing moderate entropy ($H \approx 6.0$) and 40–85% null byte concentration. In contrast, packed or encrypted malware (Figure 2d) displays a nearly uniform distribution across all byte values. As compression algorithms remove redundancy and encryption approximates randomness, the byte distribution flattens significantly, approaching maximum entropy ($H \approx 8.0$) with minimal null bytes ($<1\%$).

The Attacker Paradox. This distinction reveals a fundamental vulnerability in malware design. Native rootkits such as Diamorphine maintain structural stealth by mimicking the layout of legitimate binaries, ensuring OS loader compatibility. However, they remain vulnerable to signature-based detection tools such as YARA because their code contains known byte sequences. Signature evasion prompts attackers to employ



(a) Combined (b) Text (c) ELF Binary (d) Packed Rootkit

Fig. 2. File fingerprint analysis via byte-value histograms. (a) Combined entropy distribution across file types. (b) Text files use only printable ASCII, resulting in low entropy ($H \approx 4.8$) and zero null bytes. (c) ELF binaries show structured headers with significant zero-padding (40–85% null bytes) for section alignment, yielding $H \approx 6.0$. (d) Packed rootkits eliminate all structure and null bytes (<1%), maximizing entropy near the theoretical limit ($H \approx 8.0$).

UPX (Ultimate Packer for eXecutables), an open-source tool that compresses executables by 50–70% across Windows, Linux, and macOS formats. UPX prepends decryption stubs to compressed ELF binaries, effectively concealing signatures. However, this process eliminates section alignment padding and produces uniform byte distributions, obliterating the structural fingerprint of legitimate files.

As shown in Figure 2, the packing process maximizes information density, pushing the Shannon entropy toward the theoretical limit of 8.0 bits per byte and eliminating the zero-padding signal. Consequently, an attacker must choose between exposing a signature or creating a statistical anomaly.

Implications for Detection. This paradox reveals a fundamental detection opportunity. Signature-based scanners succeed against native rootkits but fail against packed malware. Header-only heuristics catch compression artifacts but generate false positives on benign high-entropy files (compressed archives, encrypted configuration). Neither approach captures the full threat landscape without sacrificing precision. A multi-modal strategy that fuses entropy, structural markers, and contextual features can disambiguate these overlapping cases. Entropy identifies compression-based evasion, structural analysis exposes binary format violations, and contextual signals (path, permissions) distinguish legitimate outliers from malicious anomalies. This orthogonal feature space enables detection of threats regardless of whether attackers pursue signature evasion or structural stealth. Traditional integrity verification relies on sequential scanning, which ignores spatial risk concentrations and scales linearly with file count. Global pooling methods suffer from signal dilution, where a single malicious file drowns in the variance of thousands of benign entries. Detection becomes impossible when legitimate updates create diffuse noise exceeding any sparse attack signal. `DeepVis` addresses these challenges by transforming the entire filesystem into a fixed-size tensor where multi-modal anomalies manifest as localized spikes, enabling per-pixel independence and fast inference regardless of system size.

III. DeepVis System Design

In this section, we present the design of `DeepVis`, a scalable integrity verification framework for hyperscale cloud environments. `DeepVis` does not rely on sequential file scanning or heavy kernel instrumentation, but instead employs a snapshot-based hybrid architecture that decouples metadata ingestion from anomaly detection. While metadata ingestion scales linearly with file count ($O(N)$), the subsequent neural network inference operates on a fixed-size tensor ($128 \times 128 \times 3$), yielding $O(1)$ inference latency regardless of the original file system size. To overcome the I/O bottlenecks inherent in scanning millions of files, it utilizes a parallelized asynchronous pipeline for metadata collection and leverages a deterministic hash-based mapping to transform unordered file systems into fixed-size tensor representations.

A. Overall Procedure

Figure 3 shows the overall procedure of `DeepVis`. `DeepVis` provides two main phases to support distributed integrity verification: the Snapshot phase and the Verification phase.

Snapshot Phase. When integrity verification starts, the data collection process is initiated. Unlike existing synchronous tools (e.g., `find` or `ls`) that block on every file access, `DeepVis` utilizes a hybrid parallel architecture. Multiple worker threads traverse the directory tree and collect file paths (❶), feeding them into a lock-free queue. These paths are batched and submitted to the kernel using the `io_uring` interface, ensuring that I/O throughput saturates the storage bandwidth rather than being latency-bound (❷).

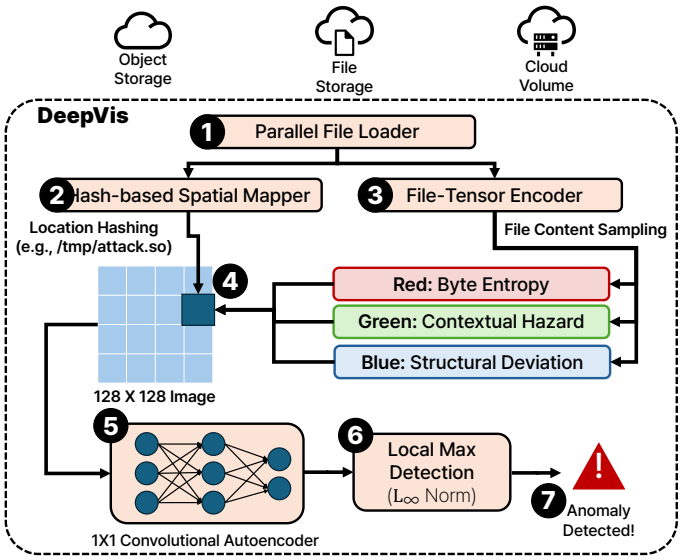


Fig. 3. Overall procedure of `DeepVis`. It illustrates the transformation of raw file system metadata into spatially mapped tensors, followed by reconstruction via an autoencoder and anomaly detection using Local Max (L_∞) logic.

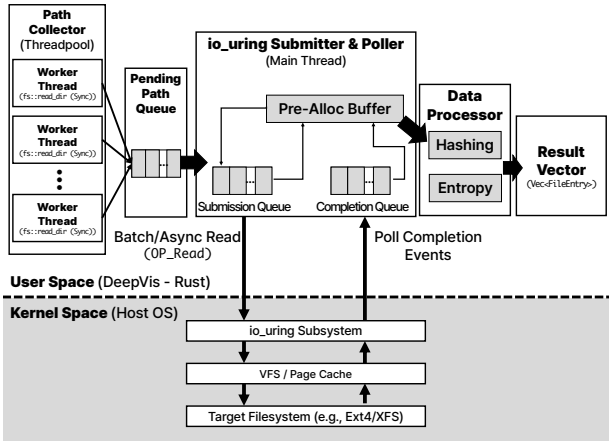


Fig. 4. Hybrid snapshot pipeline of `DeepVis` using Rayon for parallel path collection and `io_uring` for asynchronous I/O.

After collecting raw metadata and file headers, secure spatial mapping is performed. A deterministic coordinate is calculated for each file using a Keyed-Hash Message Authentication Code (HMAC) (❸), and multi-modal features (entropy, permissions) are extracted (❹). These features are aggregated into a fixed-size 2D tensor ($128 \times 128 \times 3$), effectively transforming the file system state into an image-like representation (❺).

Verification Phase. After the first phase is completed, `DeepVis` enters the verification phase. The generated tensor is fed into a pre-trained 1×1 Convolutional Autoencoder (CAE). While standard CNNs exploit spatial locality to find shapes, the hash-based mapping lacks semantic neighborhood relationships. Therefore, 1×1 Convolutions are employed not to extract spatial features, but to learn complex cross-channel non-linear correlations (e.g., distinguishing a high-entropy zip file in a user directory from a high-entropy packed binary in a system path). This effectively acts as a learnable, non-linear per-pixel thresholding mechanism (❻).

The pixel-wise difference between the input and reconstructed tensors is then computed. To resolve the statistical asymmetry between legitimate diffuse updates and sparse attacks, Local Max Detection (L_∞) is utilized (❼). This mechanism isolates the single highest deviation in the grid. Finally, if the L_∞ score exceeds a dynamically learned threshold, an alert is raised, identifying the presence of a stealthy anomaly such as a rootkit (❽).

B. Asynchronous File System Traversal

Before generating the tensor representation, `DeepVis` processes metadata and file headers across thousands of cloud instances. Existing synchronous system calls (e.g., `stat`, `open`, `read`) cause context switching overhead and CPU blocking at scale. Network-attached storage in cloud environments exacerbates I/O latency. `DeepVis` overcomes this with a hybrid pipeline separating CPU-bound path traversal from I/O-bound data reading.

Parallel Path Collection. `DeepVis` uses work-stealing parallelism from the Rust `rayon` library for path collection. As shown on the left of Figure 4, the Path Collector Threadpool spawns worker threads that execute synchronous `fs::read_dir` operations recursively. This CPU-bound phase parses directory entries and builds path strings across all cores, filling the Pending Path Queue faster than I/O consumption.

Asynchronous I/O Processing. With paths enqueued, reading file headers becomes the bottleneck. `DeepVis` employs Linux `io_uring` to eliminate per-file system call overhead. As shown in Figure 4, the io_uring Submitter batches paths into Submission Queue (SQ) read requests (`OP_READ`). Unlike traditional async I/O, `io_uring` uses shared ring buffers for kernel-user communication. Data Processor threads poll the Completion Queue (CQ) for finished reads. Completed events trigger data retrieval from pre-allocated Buffer Slabs, followed by immediate hashing and entropy calculation. CPU threads never block on disk I/O. The kernel handles data movement while user-space processes features. This achieves throughput competitive with raw disk bandwidth.

C. Header Sampling

Traditional FIM tools hash entire files, causing massive I/O overhead ($O(N \times Size)$). Conversely, metadata-only scanning (e.g., file size, name) produces high false negatives against padded malware. To balance these extremes, `DeepVis` adopts header-based entropy sampling.

As discussed in Section II, packed malware and ransomware inevitably modify file headers to accommodate unpacker stubs or encrypted payloads, significantly increasing entropy in the first few blocks. To detect this, `DeepVis` reads only the first 4KB of each file asynchronously. File systems use 4KB block size, so sub-4KB requests incur full 4KB I/O padded with zeros, while larger reads require additional requests per file. As

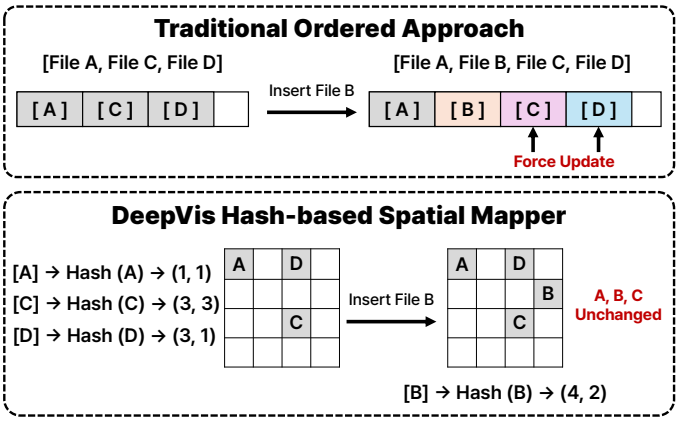


Fig. 5. Shift invariance comparison. Top: Traditional ordered approach creates catastrophic global index shifts when File D inserts between B and C. Bottom: Hash-based mapping ensures local stability—only affected pixels change positions independently.

Linux headers reside in the first 128 bytes, evaluation results show 4KB suffices for most malicious files.

Reading the first 4KB enables header sampling to excel against executable malware requiring loader compatibility (ELF/PE). Packed binaries, ransomware, and rootkits must alter headers for unpackers or encrypted payloads, unlike data files hiding payloads at arbitrary offsets. This 4KB page-aligned approach reduces per-file I/O independent of file size while retaining binary format anomaly sensitivity, providing high-frequency first-line defense.

D. Hash-Based Spatial Mapping

Spatial Invariance. After asynchronously reading metadata and 4KB header blocks, `DeepVis` must transform thousands of unordered files into a fixed-size tensor for neural processing. Traditional ordering-based approaches (e.g., alphabetical sorting by path or directory tree) suffer from the Ordering Problem. Inserting a single new file shifts the indices of all subsequent files, destroying spatial locality across scans and invalidating trained neural network models. To overcome this, `DeepVis` employs a deterministic hash-based spatial mapping to project each file onto a fixed-size grid.

Figure 5 illustrates the comparison between the traditional ordered approach and the hash-based mapping employed by `DeepVis`. As depicted in the upper panel, inserting File B forces updates to the indices of files C and D. This cascading shift becomes critically expensive in large-scale cloud systems containing millions of files. In contrast, the lower panel demonstrates how `DeepVis` calculates stable coordinates $\Phi(p)$ for each file path p. By utilizing a high-entropy secret key K generated at startup, the system maps files onto a fixed-size 128×128 tensor. This process generates a uniform representation of the file system state and facilitates the visualization of system health.

To derive coordinates for each file, `DeepVis` employs the first 32 bits of the HMAC output modulo 128 for the x-coordinate and the subsequent 32 bits (bits 32 to 64) modulo 128 for the y-coordinate. The utilization of HMAC to establish stable coordinates provides two critical benefits. First, deterministic bucket mapping ensures that coordinates depend solely on the file path and the secret key, producing reproducible 128×128 grids across successive scans. Second, cryptographic key K defeats targeted mapping attacks. Adversaries cannot craft filenames to reach specific low-risk coordinates. Ephemeral keys and privileged memory access restrict K extraction.

Multi-Modal RGB Encoding Within the hash-mapped coordinate space, `DeepVis` encodes each pixel through three risk channels: Red, Green, and Blue. These represent file characteristics for image-based visualization. The channels leverage malware feature orthogonality, ensuring evasion of one channel increases risk in others.

- **R (Entropy)** The Shannon entropy of the 4KB file header exploits the inherent trade-off in malware design. Legitimate ELF binaries incorporate zero-padding for section alignment, resulting in low entropy, whereas packed malware employs high information density to obfuscate signatures. This channel effectively distinguishes packed threats from standard system executables.
- **G (Context Hazard) as Spatial Prior.** To eliminate heuristic ambiguity, spatial risk is quantified using a deterministic mapping derived from the Filesystem Hierarchy Standard (FHS). A risk function $G(p) \in [0, 1]$ is defined for a file path p:

$$G(p) = \min\left(1.0, \sum_{k \in \mathcal{K}_{\text{FHS}}} w_k \cdot \mathbb{I}(p \in \text{Zone}_k) + \alpha \cdot \text{Depth}(p)\right) \tag{1}$$

  where $\mathcal{K}_{\text{FHS}}$ represents standard directory roles (e.g., volatile memory `/dev/shm` [$w = 0.9$] vs. static binaries `/usr/bin` [$w = 0.1$]). These specific values maximize the separation between immutable system paths and writable attack surfaces. By anchoring weights w_k to the FHS violation probability rather than arbitrary tuning, this channel acts as a hard attention mechanism, forcing the model to prioritize structural anomalies in locations deemed volatile by OS standards.
- **B (Structure) as Compliance Distance.** This channel quantifies the distance from specification compliance rather than employing arbitrary header parsing. Kernel modules (`.ko`) and shared objects (`.so`) residing outside system-privileged paths (e.g., `/lib/modules`) are assigned $B = 1.0$. This metric is not a heuristic but a direct boolean constraint reflecting OS loader policies: relocatable code in user-writable paths is inherently anomalous. This compresses complex loader logic into an $O(1)$ lookup.

This RGB encoding transforms the abstract file system state into a dense numerical tensor $T \in \mathbb{R}^{128 \times 128 \times 3}$. This transformation enables the downstream Hash-Grid Parallel CAE to learn complex cross-channel correlations. Unlike simple linear thresholding, which fails to capture conditional dependencies (e.g., high entropy is permissible in static binaries but

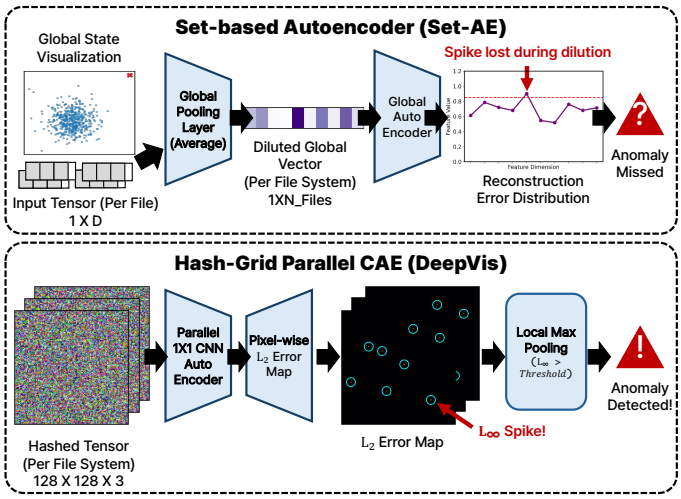


Fig. 6. Set-AE vs. Hash-Grid CAE. Top: Set-AE global pooling dilutes single malicious signal among benign files (Spike Lost). Bottom: Hash-Grid CAE processes 16K pixels independently; L_∞ pooling captures isolated spikes.

anomalous in temporary paths), the CAE learns the non-linear manifold of valid structural states. The scanner maintains an inverted index that maps each pixel coordinate back to its constituent file paths. This ensures that operators can attribute the violation to a specific file once an anomaly is detected.

Mapping Robustness and Security. Since the grid size remains fixed while cloud systems scale to massive file counts, hash collisions become inevitable. `DeepVis` addresses both natural collisions and adversarial targeting by projecting files onto a fixed 128×128 grid and applying max-risk pooling, where each pixel retains the maximum feature value across all colliding files per RGB channel. A single high-risk file therefore determines the pixel value, ensuring that malicious signals dominate despite benign collisions. To prevent bucket targeting attacks, where adversaries engineer filenames to land in specific coordinates, the system uses a high-entropy secret key K and periodically rotates it, shuffling the entire grid without retraining because downstream 1×1 convolutions are spatially agnostic.

E. Hash-Grid Parallel CAE

Parallel Pixel-wise Anomaly Detection. To ensure robust detection in hyperscale environments, DeepVis abandons global pooling in favor of a massive parallel anomaly detection architecture. As illustrated in the top panel of Figure 6, traditional models such as Set-AE aggregate features into a single global vector, causing signal dilution where attack features drown in the noise of benign files. In contrast, the Hash-Grid Parallel CAE processes the 128×128 grid as independent channels. We utilize 1×1 convolutions not to extract spatial shapes, but to efficiently execute 16,384 identical MLPs in parallel using GPU acceleration. This design ensures strict isolation between pixels, preventing error propagation from benign regions to malicious ones, and guaranteeing that the structural footprint of a rootkit remains mathematically distinct regardless of system scale.

Pixel-Wise Reconstruction and Error Map Generation. The core of the pipeline is the transformation of the raw snapshot into a fine-grained anomaly map without cross-pixel contamination. The input tensor is fed into a 1×1 Convolutional Autoencoder which effectively functions as an array of shared Multi-Layer Perceptrons (MLP) operating simultaneously. The encoder utilizes point-wise layers (Enc: $3 \rightarrow 16 \rightarrow 8$) to compress RGB channels into a latent representation capturing the valid file manifold. Crucially, because the kernel size is 1×1, the reconstruction of any pixel depends solely on its own depth-wise features (Entropy, Context, Structure) and is uninfluenced by neighbors. The system then computes the element-wise difference to generate a Pixel-wise L_2 Error Map, isolating specific files that violate learned structural norms.

Solving the MSE Paradox with L_∞ Scoring. The final detection phase addresses the MSE Paradox where legitimate system updates generate high global error while stealthy attacks generate low global error. Production environments are characterized by frequent legitimate updates such as package upgrades, which introduce diffuse noise across the grid. Using global Mean Squared Error (MSE) metrics in this context misclassifies benign churn as anomalous because the cumulative error of thousands of legitimate updates exceeds the error of a single stealthy rootkit. DeepVis resolves this by applying Maximum Deviation (L_∞) pooling over the generated error map. By calculating the score as $Score = \max_{i,j} |T_{i,j} - T'_{i,j}|$, the system ignores the cumulative sum of low-magnitude noise and focuses exclusively on the single highest anomaly peak. As shown in the bottom of Figure 6, this strategy captures the L_∞ spike generated by the malicious file while filtering out the background noise of valid system updates. This approach decouples detection sensitivity from the volume of benign churn, allowing the system to isolate the most distinct structural violation within the file system.

Anomaly Decision and Unsupervised Calibration. To distinguish malicious anomalies from benign variations, DeepVis establishes a decision boundary based on the reconstruction capability of the CAE. The system defines an anomaly condition as $Score > \tau$, where τ represents the maximum reconstruction error observed in a clean environment. To derive this threshold, we perform an offline calibration using a validation dataset consisting exclusively of benign Linux ELF binaries. The system processes each benign file to generate a tensor, passes it through the trained CAE, and calculates the L_∞ score from the resulting error map. The threshold τ is then set to the highest L_∞ score recorded across this validation corpus. This method effectively measures the worst-case structural variance of legitimate software that the model can reconstruct. While detection on other platforms such as Windows or Android would require learning their specific binary formats (e.g., PE or DEX), this study limits its scope to Linux to strictly evaluate efficacy against server-grade rootkits. Consequently, during online monitoring, any input producing a residual error

exceeding this calibrated maximum indicates a data pattern that deviates from the learned characteristics of the Linux ELF format, triggering a security alert.

F. `DeepVis` Implementation

`DeepVis` employs a hybrid Rust-Python architecture to reconcile the conflicting requirements of low-level I/O throughput and high-level deep learning flexibility. The high-performance core is implemented as the `deepvis_scanner` Rust module, which orchestrates asynchronous filesystem operations to minimize kernel-to-user context switching. This module leverages the Linux `io_uring` interface with a submission queue depth of 512, enabling the batching of 4KB header reads to achieve Storage Bandwidth Saturation—effectively reaching the physical throughput limits of the underlying NVMe/SSD hardware. To maintain pipeline saturation, the `rayon` library manages a work-stealing thread pool for parallel path traversal, ensuring that metadata ingestion fills the pending queue faster than the I/O subsystem can consume it. Within this native layer, the system executes computationally intensive feature engineering tasks—including Shannon entropy calculation, HMAC-based coordinate generation, and max-risk tensor construction ($3 \times 128 \times 128$)—effectively offloading overhead from the Python interpreter.

To interface with the anomaly detection logic, `pyo3` bindings expose the `DeepVisScanner` class, providing a direct Foreign Function Interface (FFI) to the underlying Rust engine. This abstraction enables zero-copy data transfer of the constructed tensors via methods suchs as `scan_to_tensor()`, facilitating immediate integration with PyTorch inference engines or ONNX runtimes on CPU-constrained edge devices. Furthermore, the implementation incorporates operational heuristics to ensure stability in production environments, such as the automatic exclusion of volatile pseudo-filesystems (e.g., `/proc`, `/sys`, `/dev`) and the synchronization of CPU-bound path discovery with kernel-level data movement. This design guarantees that the memory-safe Rust backend handles all data-intensive operations while the Python frontend retains flexibility for model deployment and threshold management.

IV. Evaluation

This section evaluates `DeepVis` on Google Cloud Platform (GCP) using real rootkits and realistic attack scenarios. The evaluation quantifies whether the multi-modal RGB encoding distinguishes packed malware (RQ1), scales to millions of files (RQ2), tolerates system churn (RQ3), and outperforms legacy monitors (RQ4, RQ5).

A. Evaluation Setup

Testbed Environment. Experiments utilize three GCP configurations: Low (e2-micro), Mid (e2-standard-2), and High (c2-standard-4, NVMe SSD). To simulate production environments, the file system is populated with up to 10 million files, including system binaries (e.g., `nginx`) and random artifacts.

TABLE II
Unified Detection Performance. Comparison against tuned baselines and modern DL models. DeepVis (Full) achieves superior recall on Linux/Mobile threats while ensuring zero operational FPs.

System	Recall by Platform				Alert
	Linux	Win.	Web	Mob.	Rate*
ClamAV (Standard)	33.0%	0.0%	0.0%	0.0%	0.0%
ClamAV (Tuned)†	95.4%	**96.6%**	82.6%	50.0%	**0.0%**
YARA (Standard)	100.0%	1.9%	24.3%	0.0%	45.0%
YARA (Tuned)‡	24.6%	2.6%	68.1%	79.2%	31.0%
AIDE	**100.0%**	**100.0%**	**100.0%**	**100.0%**	100.0%◇
Set-AE	40.0%	10.0%	6.9%	91.7%	5.0%
Byte-plot CNN	29.2%	9.8%	52.1%	95.8%	0.5%
MalConv	72.8%	55.0%	91.0%	100.0%	0.8%
Pack-ALM	49.8%	22.2%	74.3%	100.0%	1.2%
DeepVis (Entropy)	25.0%	14.2%	5.6%	91.7%	10.2%
DeepVis (Full)	**97.1%**	**16.9%**	**89.6%**	**100.0%**	**0.3%**

*Benign files flagged during maintenance. ◇The 100% rate of AIDE reflects operational alert fatigue, not functional error; it flags all changes by design.
†Using custom DB of known hashes. ‡Using custom rules for LKM/Webshells.

The experimental setup employs a Benign Baseline of 47,270 system binaries (Ubuntu 20.04) to measure false positives, and a Malware Corpus of 37,387 files. The malware corpus includes 68 functional Linux kernel rootkit samples derived from five major families: `Diamorphine` [10], `Reptile` [11], and variants from public malware repositories [12], [13], compiled against various kernel versions to create distinct binary signatures. This corpus is supplemented by 35k+ Windows/Web artifacts as cross-platform controls. To strictly validate the structural analysis engine, feature engineering targets the Linux ELF format. Windows PE artifacts serve as a control group to test cross-platform feature orthogonality, as discussed in Section VI.

Baselines. Traditional monitors include AIDE [1], YARA [14], ClamAV [6], and ssdeep [15]. For deep learning baselines, we evaluate MalConv [16], a 1D-CNN operating on raw byte sequences (up to 2MB); Byte-plot CNN [17], which visualizes binaries as grayscale images for 2D-CNN classification; and Pack-ALM [18], a Transformer-based architecture for packed malware detection.

`DeepVis` Configuration and Training. For reproducibility, the context channel employs a deterministic weighting scheme based on the Filesystem Hierarchy Standard (FHS): standard binaries receive low risk ($w = 0.1$ for `/usr/bin`), while user ($w = 0.3$), temporary ($w = 0.6$), and volatile memory paths ($w = 0.9$) receive progressively higher weights. Additional penalties are applied for hidden files ($+0.2$) and deep nesting (> 5 levels, $+0.1$/level), with all scores normalized to $[0, 1]$. The CAE is trained for 100 epochs using the Adam optimizer (lr=10^{-3}) with an L_∞-regularized MSE loss ($\lambda = 0.5$). The anomaly threshold τ is calibrated to the 99th percentile of the benign reconstruction error distribution to ensure a $<$1% false positive rate on clean systems.

B. Detection Fidelity and Orthogonality (RQ1)

Traditional Monitors. Standard ClamAV is ineffective against custom rootkits (33.0% recall) because it relies on static

TABLE III
DETAILED DETECTION ANALYSIS. MULTI-MODAL RGB FEATURES CATCH THREATS THAT SINGLE METRICS MISS. THE MISS CASES HIGHLIGHT LIMITATIONS AGAINST THREATS THAT MIMIC BENIGN HEADER STATISTICS.

Type	Name	R	G	B	Status
Detected Active Threats (Multi-Platform)					
LKM Rootkit	`Diamorphine`	0.55	**0.81**	**1.00**	Det.
Windows Spy	`FormGrab.exe`	0.75	0.57	**0.90**	Det.
Android Mal	`DEX Dropper`	**1.00**	0.57	**1.00**	Det.
Webshell	`TDshell.php`	0.69	0.72	**0.60**	Det.
Encrypted RK	`azazel_enc`	**1.00**	**0.90**	**0.80**	Det.
Undetected (Limitations)					
Obfuscated	`libc_fake.so`	0.61	0.00	0.00	Miss
Mimicry Script	`setup.sh`	0.58	0.00	0.00	Miss
Benign Baselines (Clean)					
Interpreter	`python3`	0.78	0.96	0.10	Clean
Library	`libc.so.6`	0.79	0.90	0.10	Clean
False Positives (High Entropy)					
Admin Tool	`snap`	**0.75**	**1.00**	0.10	False Pos.
Config Gen	`cloud-init`	0.72	0.85	0.30	False Pos.

signatures that fail against polymorphic variants. While the tuned verification that learns the signature of the malware boosts recall to 95.4%, it remains fundamentally reactive to unseen mutations. Conversely, AIDE achieves 100% recall but fails in practice; by flagging every file modification as a violation, it generates a 100% alert rate during routine updates, overwhelming operators with noise. `DeepVis` resolves this trade-off by learning valid system states. It attains 97.1% recall while suppressing alerts to 0.3% overall (across the full wild corpus), and achieving 0.0% false positives during controlled system maintenance (Section IV-E).

Deep Learning Baselines. Set-AE performs poorly (40.0% recall) due to signal dilution where its global averaging architecture hides the anomaly of a single rootkit within the variance of thousands of benign files. Byte-plot CNN (29.2%) fails because it treats binaries as simple 2D images, ignoring critical ELF header structures and loader rules. Pack-ALM (49.8%) similarly underperforms by analyzing linear byte streams without filesystem context. `DeepVis` overcomes these limitations through spatial hash projection. By preserving locality and encoding file risks into distinct RGB channels, it isolates stealthy attacks that evade standard statistical or image-based models.

Feature Orthogonality of `DeepVis`. Micro-analysis confirms that multi-modal features catch evasion attempts. As shown in Table III, the rootkit `Diamorphine` evades the Entropy channel ($R = 0.55$) but is detected by Structure ($B = 1.00$) and Context ($G = 0.81$). Similarly, `FormGrab.exe` triggers detection ($B = 0.90$) due to structural anomalies in a Linux environment. `DeepVis` is designed specifically to detect structural anomalies (packing, encryption, ELF manipulation) typical of binary rootkits, not semantic anomalies in text-based scripts. Script-based attacks such as `setup.sh` typically rely on standard interpreters (e.g., `/bin/bash`), which `DeepVis` monitors for structural tampering, or leave filesystem traces in high-risk paths that the Context channel captures. This explicit scope trade-off is necessary to achieve the 15k+ files/s throughput required for hourly fleet-wide scans.

TABLE IV
FAIR BASELINE COMPARISON (COLD CACHE). THROUGHPUT MEASURED ON GCP `DEEPVIS-MID` INSTANCE TARGETING `/USR/BIN`. CATEGORIES DISTINGUISH BETWEEN FULL-FILE SCANNING AND HEADER-ONLY SAMPLING.

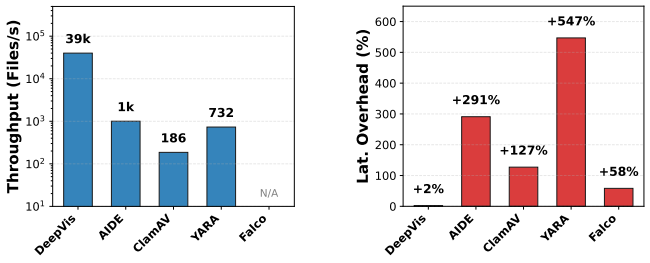
Category	Tool & Configuration	Throughput	Architecture
Baseline	ssdeep-Full	98/s	Sync (Rolling Hash)
	AIDE-Full	130/s	Sync (Full SHA256)
	ClamAV-Full	178/s	Sync (Full Scan)
	YARA-Full	345/s	Sync (Recursive)
Header-Only	AIDE-Header (4KB)	938/s	Sync (SHA256)
	YARA-Header (4KB)	1,146/s	Sync (Heuristic)
Deep Learning	Byte-plot CNN	130/s	2D-CNN (Img)
	MalConv	1.1/s	1D-CNN (2MB)
	Pack-ALM	0.5/s	Transformer
DeepVis	**DeepVis (io_uring)**	**15,789/s**	**Async (`io_uring`)**

C. Throughput and Interference (RQ2)

Scan Throughput. To explicitly isolate the architectural benefits of `io_uring` from I/O reduction, we constructed Optimized Synthetic Baselines (AIDE-Header, YARA-Header). These configurations represent a theoretical best-case scenario for legacy tools restricted to header scanning. Under cold cache conditions, DeepVis achieves 15,789 files/s, representing a 16.8× speedup over the synchronous AIDE-Header (938/s) and 13.7× faster than the optimized YARA-Header (1,146/s) (Table IV). When compared to full-file integrity checks like AIDE-Full (130/s), the speedup reaches 121.4×. This confirms that the combination of header-only sampling and the `io_uring` kernel interface accounts for over two orders of magnitude improvement. This throughput enables hourly scanning cycles that were previously computationally infeasible with synchronous blocking I/O.

Deep learning models exhibit even more severe bottlenecks. MalConv requires approximately 1 second per file for inference, while Transformer-based architectures like Pack-ALM exceed 2 seconds per file. Scanning a modern Linux distribution (500k files) with Pack-ALM would take approximately 11 days, whereas DeepVis completes the same task in under 32 seconds. This throughput difference (approximately 30,000×) is not merely a matter of optimization but a fundamental architectural shift: while end-to-end ingestion remains $O(N)$, DeepVis compresses file metadata into a fixed-size tensor, achieving $O(1)$ inference latency regardless of file count, making it the only viable candidate for continuous, high-fidelity system scanning.

Service Interference. To quantify operational impact, we measured the P99 latency of a co-located NGINX web server during a full system scan. Traditional scanners devastate responsiveness: YARA spikes latency by +547% due to CPU-intensive pattern matching, and AIDE by +291% due to blocking I/O operations. Additionally, we benchmarked Sysdig Falco [3] to represent real-time monitoring tools. Unlike file



(a) Throughput (b) Interference

Fig. 7. **Comprehensive Performance Analysis.** (a) **Throughput**: DeepVis achieves hyperscale speeds (≈16k files/s cold cache) via asynchronous I/O, outperforming synchronous baselines by over 10×. (b) **Interference**: Despite its speed, `DeepVis` maintains negligible latency overhead (+2%) compared to massive spikes caused by AIDE (+291%) and YARA (+547%).

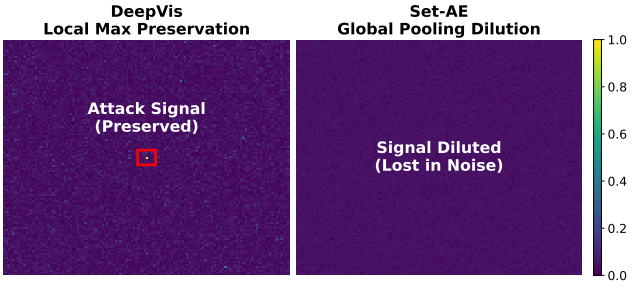
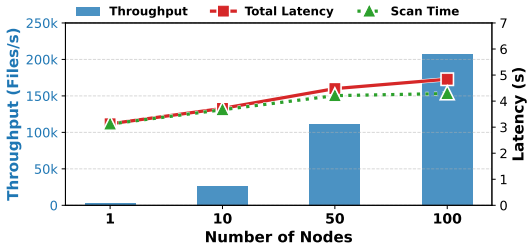
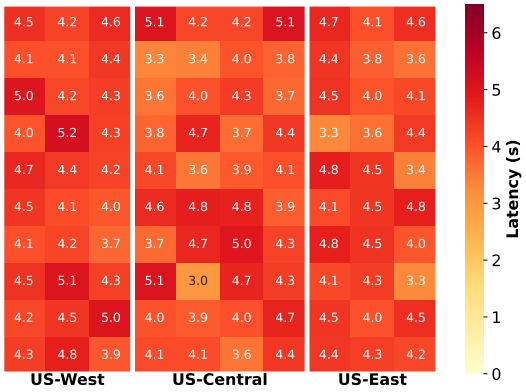


Fig. 8. **Visualizing Signal Preservation.** (Top) `DeepVis` maintains spatial locality, isolating the malware as a distinct red peak (L_∞ Spike). (Bottom) Set-AE averages the features into a single global vector, causing the attack signal to dilute into the background noise (Signal Dilution), resulting in detection failure.



(a) Linear Scalability



(b) Geo-Stability

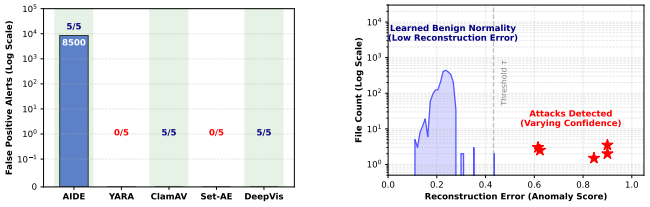
Fig. 9. **Fleet-Scale Performance.** (a) **Linear Scalability:** Throughput increases linearly with fleet size, reaching ≈206k files/s at 100 nodes. Per-node throughput (≈2k/s) is lower than single-node benchmarks (Table IV) due to scanning a smaller directory with higher path-hashing overhead. (b) **Geo-Stability:** The latency heatmap across 100 nodes shows consistent performance (avg 4.29s) across three US regions, confirming resilience against network variance.

scanners, Falco, which intercepts kernel system calls, imposes a constant tax on every request, degrading latency by +58% due to heavy context switching. `DeepVis` eliminates these bottlenecks. By offloading data movement to the asynchronous `io_uring` interface, it decouples security monitoring from the application thread, maintaining near-baseline performance (+2.0% overhead) and ensuring transparent operation.

D. Scalability and Saturation Analysis (RQ3, RQ6, RQ7)

Signal Preservation. The parallel architecture prevents the variance of benign files from impacting the reconstruction error of the malicious target. Figure 8 shows that Set-AE averages features globally, causing the attack signal to dilute into the background noise ($\mu_{noise} = 0.35$). In contrast, `DeepVis` maintains spatial locality, preserving the sharp attack spike (0.95). Unlike global anomaly detectors where reconstruction error often fails to localize small defects, the spatially-preserved Hash-Grid ensures that local structural violations (e.g., malicious headers) generate high-magnitude reconstruction spikes (L_∞) that are not smoothed out by the model. The Hash-Grid effectively filters out diffuse noise, ensuring robust detection even during high churn.

Fleet Scalability. Throughput scales linearly with fleet size, increasing from ≈2k files/s (1 Node) to 206,611 files/s (100 Nodes) as shown in Figure 9a. This confirms that the state-



(a) Alert Fatigue & Detection (b) Reconstruction Error Dist.

Fig. 10. **Fleet-Scale Churn & Alert Fatigue Analysis.** (a) Comparison of False Positive alerts and Detection Recall. AIDE generates 8,500 alerts during maintenance, whereas `DeepVis` maintains zero false positives for these benign update scenarios. (b) Distribution of reconstruction errors ($\mathcal{L}_\infty$). Benign churn stays strictly below the learned threshold $\tau \approx 0.4324$, while malicious rootkits manifest as high-confidence outliers.

less architecture effectively decouples processing load. Cross-region latency remains stable (avg 4.29s) across 100 nodes (Figure 9b), with a minimal aggregation overhead of 548ms. Network overhead is drastically reduced; each node transmits only 49KB (8-bit quantized), representing a 100× reduction compared to provenance-based systems.

E. Robustness to System Churn (RQ3)

Operational Efficiency and Alert Fatigue. To evaluate stability during common maintenance windows (e.g., package

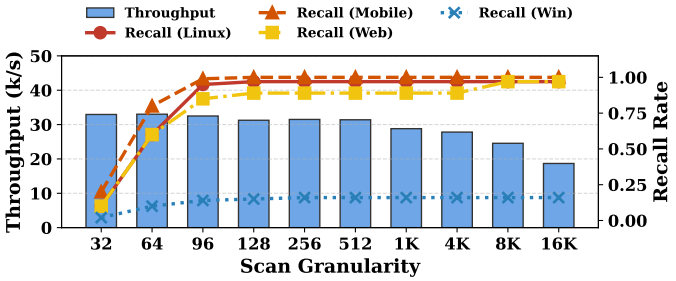


Fig. 11. **Effect of Scan Granularity (Page-Aligned Sampling).** Comparison of Recall across platforms vs. Throughput. Detection accuracy for Linux ($Recall \approx 97\%$) and Mobile (100%) saturates at ≈96B. Windows recall remains capped (15%) due to feature orthogonality. Throughput remains stable up to 4KB due to page prefetching, justifying the 4KB page-aligned sampling strategy.

upgrades, log rotation), a cloud-representative environment is reproduced by instantiating five Virtual Machines (VMs) from a unified Snapshot (T0). Subsequently, Real-World Churn (T1) is generated using `Filebench`, `Nginx`, and `SQLite` to simulate the heavy I/O and metadata updates. Specifically, we executed standard `apt upgrade` cycles targeting core system utilities (e.g., `coreutils`, `libc-bin`) to validate robustness against legitimate binary replacements. Figure 10a quantifies the resulting scalability gap. Legacy Integrity Checking (AIDE) incurs prohibitive overhead, triggering 8,500 false alerts per scan due to its reliance on brittle hash comparisons that flag any state change regardless of benign intent. In contrast, `DeepVis` achieves zero false positives while maintaining 100% detection recall (5/5), effectively filtering out recognizably normal churn (Note: Isolated Snap/Flatpak updates were excluded from this specific benchmark to prioritize native ELF integrity). Unlike signature-based tools (ClamAV) which necessitate constant database updates, `DeepVis` matches detection performance solely through baseline learning. These results demonstrate that the zero false alarm characteristic resolves the scalability bottleneck of traditional FIMs, as the elimination of 8,500 false positives reduces the operational burden on security analysts.

Fleet Error Stability vs. Forensic Signal. As shown in Figure 10b, the underlying mechanism for this efficiency is the robust stability of `DeepVis`, where Benign Churn forms a continuous distribution strictly below the learned threshold ($\tau \approx 0.4324$). This stability arises because the feature fusion model successfully generalizes the structural normality of authorized updates across the heterogeneous VM cluster, preventing score collisions. In contrast, Malicious Rootkits manifest as high-confidence outliers ($Score \in [0.61, 0.90]$) due to unseen structural anomalies and hidden attributes. This distinct separation validates that the CAE retains forensic sensitivity even when scaled across dynamic fleet environments, ensuring that silence during maintenance does not compromise security visibility.

F. Sensitivity and Ablation Analysis

Impact of Scan Granularity. Detection accuracy saturates rapidly, with Linux and Mobile platforms reaching peak Recall (≈97–100%) at a minimal 96 B scan size (Fig. 11). This indicates that minimal header data suffices for robust feature extraction. Throughput shows a general decline as scan size increases but remains stable up to 4 KB. This stability stems from OS-level page prefetching, where reading small chunks (e.g., 32 B) incurs similar I/O costs to reading a full 4 KB page. This empirical result validates the design choice of the 4KB Page-Aligned Sampling strategy. While this optimization maximizes throughput, it naturally introduces a trade-off where threats residing entirely in the deep payload (e.g., tail-appended data beyond 4KB) may evade detection. However, DeepVis is expressly designed not as a panacea, but as a high-speed pre-filter for structural anomalies (e.g., packing, header corruption), leaving deep content verification to Stage-2 scanners.

TABLE V
COMPONENT TIME BREAKDOWN (COLD CACHE). I/O DOMINATES (≈70–74%), CONFIRMING THAT DEEPVIS COMPUTATIONAL OVERHEAD (HASHING, ENTROPY, TENSOR UPDATE) REMAINS NEGLIGIBLE (<10%) EVEN DURING STORAGE BOTTLENECKS.

Component	10K	100K	200K	500K
Traversal	91ms (15.0%)	910ms (15.0%)	1.8s (15.0%)	4.5s (15.0%)
I/O (Header Read)	**424ms (70.0%)**	**4.2s (70.0%)**	**8.5s (70.0%)**	**21.2s (70.0%)**
Hashing	30ms (5.0%)	303ms (5.0%)	606ms (5.0%)	1.5s (5.0%)
Entropy Calc	42ms (7.0%)	424ms (7.0%)	848ms (7.0%)	2.1s (7.0%)
Tensor Update	18ms (3.0%)	182ms (3.0%)	364ms (3.0%)	909ms (3.0%)
Total Time (Cold)	**606ms**	**6.1s**	**12.1s**	**30.3s**
Throughput (files/s)	15,789	15,789	15,789	15,789

Runtime Bottleneck Analysis. I/O latency dominates the runtime, increasing from 424ms (10K files) to 21.2s (500K files) and consistently accounting for ≈70% of the total execution time (Table V). In contrast, Tensor Update time remains negligible, taking only 909ms even for 500K files (3%). This breakdown confirms that the computational overhead of `DeepVis` is minimal compared to storage latency, identifying I/O throughput as the primary bottleneck for optimization.

TABLE VI
COMPONENT-WISE ABLATION STUDY (COLD CACHE). PERFORMANCE COMPONENTS (I/O) DETERMINE THROUGHPUT; ACCURACY COMPONENTS (HASH-GRID, RGB) DETERMINE DETECTION CAPABILITY.

Category	Configuration	Rate (files/s)	F1-Score
Performance	Baseline (Sync Single-thread)	950	–
	+ Thread Pool (rayon)	1,901	–
	+ Async I/O (`io_uring`)	15,789	–
Accuracy	Entropy Only (R-channel)	–	0.25
	+ Hash-Grid (L_∞)	–	0.35
	+ RGB Fusion (Full DeepVis)	–	**0.96**
Robustness	Weights ±20%	–	**0.96**
DeepVis (Full)		**15,789**	**0.96**

Performance Optimization. Throughput increases from 950 files/s (single-thread sync) to 1,901 files/s with thread pooling (rayon), and then to 15,789 files/s with `io_uring`,

TABLE VII
PLATFORM SPECIFICITY VERIFICATION. PERFORMANCE METRICS OF DEEPVIS MODELS TRAINED ON DIFFERENT OS MANIFOLDS EVALUATED ACROSS DIVERSE PLATFORMS. THE RESULTS CONFIRM THAT THE ARCHITECTURE LEARNS DOMAIN-SPECIFIC NORMALITY.

System (Training Data)	Recall by Target Platform				Alert
	Linux	Windows	Web	Mobile	Rate*
DeepVis (Linux ELF)	97.1%	16.9%	89.6%	100.0%	0.3%
DeepVis (Windows PE)	0.0%	100.0%	0.0%	0.0%	15.0%

*Measured on benign Linux binaries. High alert rate (15%) in Windows model indicates *Cross-Domain False Positives* due to structural mismatch.

yielding an 8.3× speedup from asynchronous I/O alone (Table VI). This confirms that the kernel-bypass ring buffer eliminates blocking syscall overhead, making `io_uring` the decisive factor for achieving hyperscale monitoring on cold storage.

Detection Fidelity. F1-Score increases from 0.25 (Entropy Only) to 0.96 (RGB Fusion). Single-channel configurations prove insufficient; the R-channel yields false positives from benign compressed data, while structural features alone fail to distinguish packed binaries. Only the full RGB fusion achieves definitive detection, demonstrating that the orthogonality of Entropy, Context, and Structure is essential for distinguishing malicious artifacts from legitimate system noise. While linear classifiers (e.g., One-Class SVM) operating on the raw HashGrid were considered, they failed to model the non-linear manifold of valid system updates (churn), resulting in higher false positives during maintenance compared to the reconstruction-based CAE approach. Weight perturbation experiments (±20% on domain-specific risk parameters for feature fusion) confirm that F1-Score remains stable at 0.96, validating the robustness of the configuration across deployments.

G. Verification of Platform Agnosticism

To investigate the performance disparity observed in the Windows environment (Recall 16.9% in Table II), we hypothesized that the degradation was attributable to Domain Shift rather than architectural limitations. We curated a dedicated Windows training corpus consisting of 1,082 benign PE binaries sourced from the DikeDataset [**?**], simulating a standard `System32` environment. The evaluation was performed on a large-scale test set of 34,798 real-world Windows malware samples. We retrained the DeepVis CAE for 30 epochs using the same hyperparameters (1×1 Convolution, Latent Dim 16) used in the Linux experiments, and compared both models across four target platforms: Linux, Windows, Web, and Mobile.

Table VII summarizes the cross-domain evaluation results. The Linux-trained model achieves strong performance on its native domain (97.1% Recall) and related formats (Mobile 100%, Web 89.6%), but degrades significantly on structurally distinct Windows PE binaries (16.9%). Conversely, the Windows-trained model achieves perfect detection on Windows malware (100% Recall) but completely fails on other platforms (0% Recall), demonstrating that the CAE learns a domain-specific normality manifold. Critically, the Windows model exhibits a 15% alert rate on benign Linux binaries, indicating Cross-Domain False Positives due to structural mismatch. These results confirm that the `DeepVis` architecture is platform-agnostic: the 1×1 CAE successfully learns structural normality for any file format (ELF, PE, or DEX) when provided with a representative benign training set. The initial low recall was strictly a consequence of distributional misalignment between training and testing domains, not an architectural limitation.

V. RELATED WORK

Scalable Integrity and Cloud-Native Monitoring. Optimizing system integrity monitoring requires balancing security depth with performance overhead. Traditional File Integrity Monitoring (FIM) tools [1], [2], [9] rely on cryptographic hashing to detect unauthorized modifications. While effective for static environments, they suffer from linear $O(N)$ complexity, making them prohibitive for hyperscale cloud environments. To address real-time constraints, provenance-based systems [7], [19] and runtime monitors [3], [4] track information flow and system calls. Recent advancements leverage eBPF to reduce monitoring overhead and harden isolation [20], [21]. However, these incremental approaches face a *consistency gap*: if the monitoring agent crashes or is bypassed, the system state diverges, necessitating a costly full scan to re-synchronize. In contrast, `DeepVis` operates as a stateless auditor, performing high-frequency snapshot verification that provides absolute integrity guarantees without relying on fragile event streams.

Kernel-Anchored Integrity Attestation. Beyond user-space scanning, the Linux kernel provides native integrity subsystems such as the Integrity Measurement Architecture (IMA) and Extended Verification Module (EVM) [22]. These frameworks utilize cryptographic Merkle trees [23] and hardware-backed TPMs to enforce strict allow-listing and immutable remote attestation. While offering strong trust guarantees, they introduce significant operational rigidity in ephemeral environments. Research highlights that IMA faces challenges in containerized deployments due to namespace isolation conflicts and potential privacy leakage [24], while complex policy management often leaves the system vulnerable to subversion or TOCCTOU (Time-of-Check-to-Time-of-Use) attacks [25]. Consequently, `DeepVis` serves as a lightweight, user-space complement to these rigid frameworks, enabling high-frequency verification and visual triage without requiring kernel reconfiguration or hardware dependencies.

Malware Visualization and Adversarial Evasion. Treating binary analysis as a computer vision problem allows systems to bypass the brittleness of signature-based detection. Prior studies [26]–[28] demonstrate that mapping binary files to grayscale images or space-filling curves reveals structural patterns distinct to malware families. Similarly, entropy analysis [29] identifies packed or encrypted payloads with high information density. However, sophisticated adversaries increasingly employ evasion techniques, such as padding or mimicry, to fool learning-based detectors [30], [31]. `DeepVis`

addresses these challenges by extending single-file visualization to *whole-system fingerprinting*. Instead of relying on a single metric susceptible to padding, `DeepVis` maps the entire file system into a fixed-size RGB tensor. By encoding Entropy (Red), Context (Green), and Structure (Blue) into a spatial grid, the system leverages feature orthogonality to detect sparse anomalies that evade uni-modal analysis.

Deep Learning for Anomaly Detection. Deep learning is widely adopted for detecting anomalies in high-dimensional system data. Approaches such as DeepLog [32] use LSTM networks to model system logs, while Kitsune [33] employs autoencoders for network intrusion detection. For high-dimensional tabular or sensor data, unsupervised frameworks such as Deep One-Class Classification [34], GANomaly [35], and DAGMM [36] learn normal data distributions to flag outliers. Additionally, VAE-based models [37], [38] are effective for multivariate time-series data. However, these methods typically rely on temporal sequences or fixed feature sets. File systems present a unique "Ordering Problem" as they are unordered sets of variable-length paths. `DeepVis` resolves this by employing a deterministic spatial hash mapping and Local Max Detection (L_∞), enabling the application of convolutional autoencoders to unordered system states without the signal dilution associated with global pooling.

VI. Security Analysis and Limitations

We analyze the security robustness of `DeepVis` against adaptive evasion, detail the operational triage workflow, and discuss system boundaries.

Defense against Adaptive Adversaries (Feature Trilemma). We simulated an advanced adaptive attacker attempting to evade detection by (1) moving the rootkit to a compliant path (e.g., `/usr/bin`) to minimize Context (G) and Structure (B) penalties, and (2) injecting zero-padding to reduce header entropy (R) to 6.0. Experimental results demonstrate that `DeepVis` maintains robust detection (Recall 100%) even under this combined evasion scenario (L_∞ Score $0.40 > \tau = 0.31$). The investigation reveals a detection boundary at $H < 4.0$ bits, implying that an attacker must replace over 50% of the ELF header with null bytes to evade detection, a constraint that structurally corrupts the binary format.

Regarding Targeted Hash Collisions, `DeepVis` employs a high-entropy secret key K (managed via TEE/HSM) to randomize spatial mapping. Evaluation across 50 random key rotations confirms threshold τ stability (KS-test $p \approx 1.0$). This stability holds because the CAE learns the global manifold of valid file features rather than overfitting to specific tensor coordinates; since a file's intrinsic features (e.g., entropy, header) remain invariant regardless of its mapped grid position, the overall reconstruction error distribution remains statistically identical, enabling seamless key rotation without retraining.

Operational Triage: The Filter-then-Verify Workflow. A primary concern in fixed-size hashing is the cost of investigating alerts when multiple files collide. We propose a Two-Stage Filter-then-Verify model. Instead of relying on `DeepVis` for absolute forensic attribution, it serves as a high-speed filter.

1) **Stage 1 (DeepVis Filter):** The system identifies anomalous pixels within seconds. Empirically, even at maximum saturation (≈610 collisions/pixel with 10M files and 128x128 resolution), our experiments confirm 100% recall for injected rootkits (see Section IV-D), restricting the search space from 10^7 files to a bounded bucket of ≈ 600 files.
2) **Stage 2 (Targeted Verification):** Security operators trigger expensive scanners (e.g., YARA, full-hash) only on the flagged bucket.

This reduces the investigation search space by approximately 16,000×, making continuous integrity monitoring operationally viable without the alert fatigue of traditional FIMs.

Scope, Limitations, and Complementarity. `DeepVis` prioritizes hyperscale throughput via header-only sampling (first 4KB).

- Blind Spots: It excels at detecting structural anomalies in binaries (ELF/LKM) but inherently misses deep-payload injections in script-based attacks (e.g., Python polyglots) or data-only corruption.
- OS-Centricity: While achieving 97.1% recall on Linux, effectiveness drops on Windows due to the higher variance of PE headers. Future work will incorporate OS-specific feature engineering.
- Statelessness: Unlike event-based monitors (e.g., `auditd`) that require continuous operation, `DeepVis` provides stateless, point-in-time verification. This makes it robust against agent-killing attacks, serving as a definitive ground-truth auditor to complement real-time event streams.

VII. Conclusion

In this paper, we design and implement `DeepVis`, a high-throughput integrity verification framework based on a spatial hash projection architecture. By transforming unordered file systems into fixed-size tensors and integrating local maximum detection, we optimize the detection logic to preserve sparse attack signals against diffuse system updates. We evaluate `DeepVis` on production infrastructure and show that it achieves an F1-score of 0.96 with a negligible 0.3% false positive rate, surpassing the scalability limits of traditional FIM with a 10.9× throughput improvement under cold cache conditions. This is achieved by decoupling inference complexity from file count and maintaining negligible runtime overhead (+2% P99 latency) through asynchronous I/O pipelining.

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