

# Detecting and Preserving Digital Evidence in Decentralized Multi-Cloud and Serverless Environments

Aditya Agrawal, Abhishek, Yash Ranjan Bhargav

Student, National Institute of Technology, Kurukshetra  
Department of Computer Engineering

**Abstract-** The rapid adoption of multi-cloud and serverless architectures has fundamentally altered how digital evidence is generated, distributed, and lost, creating significant challenges for contemporary digital forensic investigations. Current cloud forensic practices remain largely provider-specific and assume stable infrastructure, leaving investigators without reliable mechanisms to detect, preserve, and correlate volatile forensic artifacts across decentralized cloud environments. As a result, critical evidence such as execution logs, transient identifiers, and ephemeral state information is frequently incomplete, inconsistent, or legally fragile. This paper presents a provider-agnostic forensic framework designed to support systematic detection, acquisition, and preservation of digital evidence in multi-cloud and serverless deployments. The proposed approach introduces a canonical event model, cross-provider log normalization, and a coordinated snapshotting strategy to capture transient artifacts while maintaining evidentiary integrity and provenance. Event correlation is achieved through time-aligned stitching of heterogeneous logs, enabling accurate reconstruction of distributed execution timelines. A prototype implementation was evaluated across simulated multi-cloud environments incorporating serverless workloads from multiple providers. Experimental results demonstrate improved evidence completeness and correlation accuracy compared to baseline cloud-native acquisition methods, while introducing minimal operational overhead. The findings indicate that standardized, cross-cloud forensic mechanisms are both feasible and necessary, offering practical guidance for investigators and cloud service consumers seeking legally defensible forensic readiness in decentralized cloud infrastructures.

**Keywords:** Digital forensics, multi-cloud, serverless, cloud forensics, evidence preservation, log correlation, snapshotting, chain of custody, provenance.

## I. INTRODUCTION

### Motivation and Real-World Context

Cloud computing has evolved from isolated, single-provider deployments into heterogeneous multi-cloud and serverless ecosystems. Enterprises increasingly distribute workloads across multiple cloud service providers (CSPs) to achieve vendor independence, regulatory compliance, geographic redundancy, and cost optimization. At the same time, serverless computing models—such as Function-as-a-Service (FaaS)—have become dominant for event-driven and microservice architectures due to their elasticity and reduced operational overhead.

This architectural shift fundamentally alters the location, lifetime, and ownership of digital artifacts.

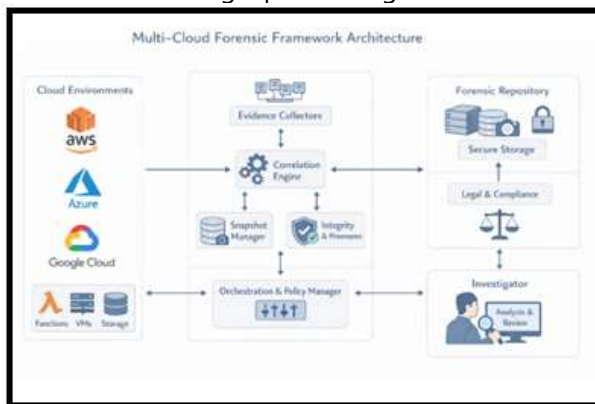
Execution environments are dynamically instantiated, logs are generated across independent control planes, and infrastructure components may exist only for milliseconds. Traditional digital forensic assumptions—persistent hosts, stable storage, and centralized logging—no longer hold in such environments.

From an investigative standpoint, this creates a significant gap. Security incidents, insider misuse, data exfiltration, and policy violations increasingly occur in cloud-native systems, yet investigators lack reliable, standardized mechanisms to detect, collect, and preserve evidence across multiple cloud providers while maintaining forensic soundness.

## B. Forensic Challenges in Multi-Cloud and Serverless Environments

Digital forensics in decentralized cloud infrastructures faces several systemic challenges:

1. **Ephemerality of Evidence:** Serverless functions and containerized workloads are short-lived. Memory state, execution context, and temporary storage are often destroyed immediately after execution, leaving minimal forensic residue.
2. **Distributed Control and Ownership:** Evidence is fragmented across customer-managed resources and provider-controlled infrastructure. Investigators have limited visibility into hypervisor-level data, internal scheduling metadata, and provider-side logs.
3. **Heterogeneous Logging Interfaces:** Each CSP exposes logs using distinct schemas, retention policies, timestamps, and access mechanisms. Correlating events across providers requires manual normalization and is prone to inconsistency.
4. **Time Synchronization and Causality:** Logs generated by independent cloud control planes may exhibit clock drift and inconsistent ordering, complicating timeline reconstruction and causal inference.
5. **Legal and Admissibility Constraints:** Without verifiable provenance, integrity guarantees, and a documented chain of custody, cloud-derived evidence may fail to meet admissibility standards in legal proceedings.



These challenges collectively render existing forensic tools insufficient when applied directly to multi-cloud or serverless deployments.

## C. Problem Statement

Despite widespread adoption of multi-cloud and serverless architectures, there is no unified forensic framework capable of reliably detecting, correlating, and preserving digital evidence across heterogeneous cloud providers while ensuring forensic integrity and legal admissibility.

Current approaches rely on provider-specific exports, manual log analysis, or post-incident data requests, all of which are incomplete, non-deterministic, and vulnerable to evidence loss. A systematic, provider-agnostic method is required to capture transient artifacts, align distributed logs, and preserve evidence with verifiable provenance.

## D. Research Questions

This work addresses the following research questions:

- **RQ1:** How can transient forensic artifacts be reliably detected and collected in multi-cloud and serverless environments before they are lost?
- **RQ2:** What mechanisms can accurately correlate heterogeneous logs and events across independent cloud providers?
- **RQ3:** How can evidence integrity, provenance, and chain of custody be preserved in decentralized cloud infrastructures?
- **RQ4:** What is the performance and scalability impact of such forensic mechanisms on production cloud workloads?

## E. Research Contributions

This paper makes the following contributions:

- A provider-agnostic forensic framework for detecting and preserving evidence in multi-cloud and serverless environments.
- A canonical log normalization and correlation model enabling cross-provider event reconstruction.
- A coordinated snapshot and acquisition protocol designed to capture ephemeral cloud artifacts with minimal service disruption.
- An integrity and provenance mechanism supporting cryptographic verification and chain-of-custody preservation.

- An experimental evaluation using realistic multi-cloud scenarios, measuring detection accuracy, correlation precision, and acquisition overhead.
- A forensic and legal analysis discussing admissibility, jurisdictional constraints, and compliance considerations.

### F. Evidence Correlation Model

To reconstruct distributed event timelines, events are modeled as normalized tuples:

$$E = \langle t, s, r, a, h \rangle$$

Where,

**t** denotes the normalized timestamp,

**s** the source provider,

**r** the resource identifier,

**a** the action performed, and

**h** a cryptographic hash ensuring integrity.

This representation enables deterministic ordering and correlation across heterogeneous logging systems.

### G. Comparative Overview of Cloud Forensic Challenges

Table I summarizes key forensic challenges across cloud deployment models.

| Environment Type  | Evidence Persistence | Log Uniformity | Acquisition Complexity |
|-------------------|----------------------|----------------|------------------------|
| Single-Cloud IaaS | High                 | Moderate       | Medium                 |
| Multi-Cloud IaaS  | Medium               | Low            | High                   |
| Serverless (FaaS) | Very Low             | Low            | Very High              |

## II. BACKGROUND AND PRELIMINARIES

### A. Cloud Computing Models Overview

Cloud computing environments are commonly categorized based on the abstraction level at which computing resources are exposed to users. Each model introduces distinct forensic visibility and control challenges.

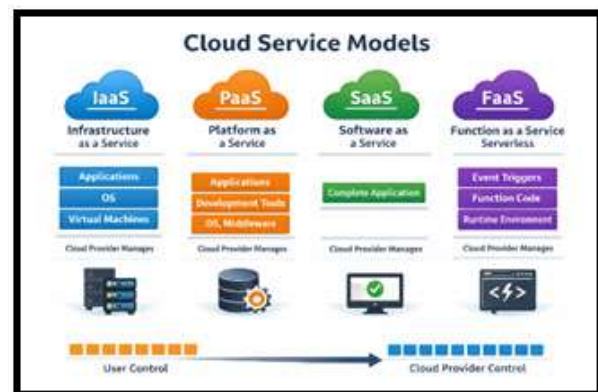
Infrastructure as a Service (IaaS) provides virtualized compute, storage, and networking resources. Users retain control over guest operating systems and deployed applications, allowing limited traditional

forensic techniques such as disk imaging or memory acquisition. However, physical infrastructure and hypervisor-level artifacts remain inaccessible to investigators.

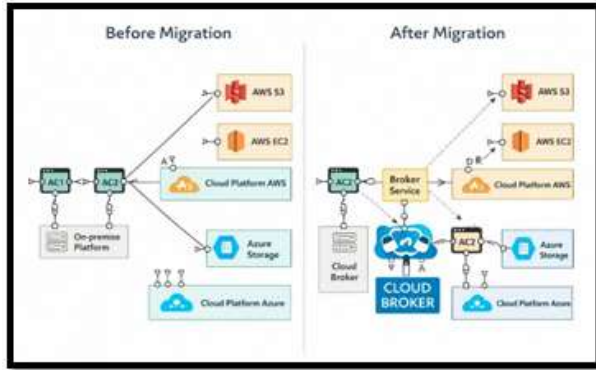
Platform as a Service (PaaS) abstracts the operating system and runtime environment. While application-level logs and configuration metadata may be available, system-level artifacts are typically opaque. Forensic reconstruction in PaaS environments therefore relies heavily on provider-generated audit logs and application telemetry.

Function as a Service (FaaS) / Serverless computing represents the most abstracted execution model. Compute instances are ephemeral, stateless, and instantiated on-demand. Execution environments are short-lived, often lasting milliseconds, which significantly constrains post-incident evidence acquisition. Persistent forensic artifacts are limited primarily to logs, invocation metadata, and downstream service interactions.

Hybrid cloud architectures integrate on-premises infrastructure with public cloud services, whereas multi-cloud deployments distribute workloads across multiple independent providers. These models complicate forensic analysis due to heterogeneous logging formats, inconsistent retention policies, and lack of a unified trust or time reference.



The figure shows IaaS, PaaS, SaaS, and FaaS, illustrating the increasing level of abstraction and the corresponding shift of control from users to cloud providers as services become more managed.



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### B. Forensic Concepts and Standards

Digital forensics in cloud environments is governed by foundational principles that ensure evidence reliability and legal defensibility.

Chain of custody refers to the documented, chronological record of evidence handling from acquisition to presentation. In distributed cloud systems, maintaining chain of custody is non-trivial due to automated evidence collection, third-party provider involvement, and cross-jurisdictional data movement.

Integrity ensures that collected artifacts remain unaltered. Cryptographic hashing and secure timestamping are commonly employed, yet their effectiveness depends on trustworthy acquisition points and verifiable provenance.

Admissibility concerns whether evidence satisfies legal standards of authenticity, relevance, and reliability. Cloud-derived evidence may be challenged due to shared infrastructure, lack of physical access, or provider-controlled acquisition mechanisms.

International guidance for digital evidence handling is provided by standards such as ISO/IEC 27037, which outlines principles for identification, collection, acquisition, and preservation of digital evidence, and ISO/IEC 27050, which addresses electronic discovery processes. While these standards are technology-agnostic, they offer limited operational guidance for decentralized and

ephemeral cloud environments, particularly serverless platforms.

### C. Cloud Provider Logging and Tooling

In the absence of direct access to physical or virtual infrastructure, cloud forensics relies predominantly on provider-generated telemetry. Common categories of forensic-relevant logs include:

- Audit and control-plane logs, capturing administrative actions such as identity management, configuration changes, and API invocations.
- Execution and application logs, recording runtime behavior of applications or functions, including invocation identifiers and error traces.
- Network flow logs, summarizing traffic metadata such as source/destination addresses, ports, and timestamps without payload visibility.
- Storage and object metadata, including access timestamps, version histories, and integrity checksums.

Table I — Common Cloud Log Types and Forensic Utility

| Log Category      | Primary Contents        | Forensic Value                       | Key Limitation                |
|-------------------|-------------------------|--------------------------------------|-------------------------------|
| Audit Logs        | API calls, IAM actions  | Attribution, timeline reconstruction | Provider-controlled retention |
| Execution Logs    | Function/runtime output | Behavior analysis                    | Ephemeral availability        |
| Network Flow Logs | Traffic metadata        | Lateral movement detection           | No payload visibility         |
| Storage Metadata  | Object access, versions | Data access tracing                  | Limited contextual detail     |

The diversity of log schemas and retention policies across providers necessitates normalization and correlation mechanisms for effective multi-cloud investigations.

### D. Definitions and Notations

For clarity and consistency, the following terms are used throughout this work:

- **Artifact (A):** Any discrete digital object with potential evidentiary value, such as a log entry, configuration snapshot, or metadata record.
- **Event (E):** A time-bound occurrence representing an action or state change within the cloud environment.
- **Snapshot (S):** A point-in-time capture of system state, including data, configuration, and metadata.
- **Provenance tuple (P):** A structured record describing the origin, context, and handling of an artifact.

Formally, an event can be represented as:

$$E = \langle id, t, s, a, m \rangle$$

Here, *id* is a unique identifier, *t* denotes timestamp, *s* represents the source entity, *a* is the performed action, *m* captures associated metadata.

A provenance tuple for an artifact *A* is defined as:

$$P(A) = \langle origin, acquisition\_method, hash, t_{acq}, custodian \rangle$$

This formalization enables systematic reasoning about evidence integrity, correlation, and chain of custody across decentralized cloud environments.

### III. RELATED WORK

#### A. Traditional cloud forensics (single-provider approaches).

Early cloud forensic research primarily targets single-provider environments, leveraging provider-native audit logs, VM disk exports, and storage snapshots to acquire evidence. These methods benefit from high-fidelity artifacts and mature APIs but remain tightly coupled to provider-specific semantics and retention policies. Consequently, they offer limited support for cross-provider investigations and are ineffective when transient resources or short log retention windows are involved.

#### B. Multi-cloud and cross-platform forensic research.

Multi-cloud forensics extends these approaches by addressing heterogeneity across providers, focusing on schema normalization, adapter-based acquisition, and coordinated snapshot orchestration. Prior work proposes canonical event models and

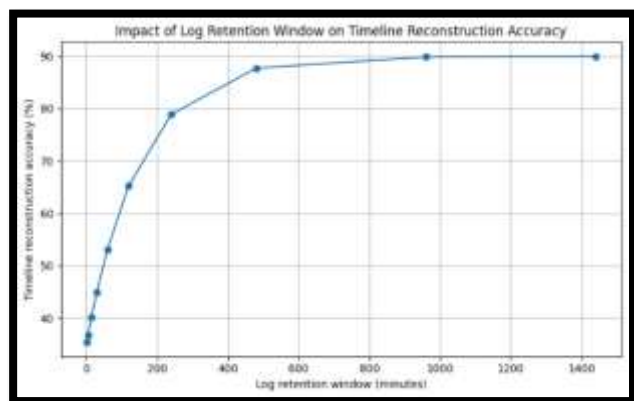
translation layers to unify disparate logs; however, semantic loss, API evolution, and clock inconsistencies remain unresolved challenges. Most proposed solutions are evaluated in controlled environments and lack validation at production scale.

#### C. Serverless-specific forensic studies.

Serverless platforms introduce additional complexity due to the ephemeral nature of function execution and the absence of persistent runtime state. Existing studies explore passive collection of invocation logs and active instrumentation through wrappers or middleware. While active techniques improve observability, they introduce performance overhead and trust concerns, whereas passive methods often fail to capture sufficient causal context for reliable reconstruction.

#### D. Log correlation, provenance, and time synchronization approaches.

Log correlation techniques typically combine temporal proximity, identifier similarity, and contextual metadata to infer causal relationships across events. Provenance models based on graphs or cryptographic chaining enhance integrity and traceability but impose non-trivial storage and computational overhead. Time synchronization remains a limiting factor, as clock drift and inconsistent timestamp semantics across providers degrade correlation accuracy, particularly in short-lived executions.



The graph shows that timeline reconstruction accuracy increases rapidly with small increases in log retention, but levels off as retention becomes longer,

indicating diminishing returns beyond moderate retention windows.

Impact of log retention window on timeline reconstruction accuracy. The synthetic experiment illustrates diminishing returns: modest increases in log retention substantially improve reconstruction accuracy, while longer retention periods yield marginal gains. Prior studies indicate that limited log retention severely constrains post-incident timeline reconstruction. As abstracted in above graph, extending retention from minutes to a few hours yields significant gains in reconstruction accuracy, whereas further extensions offer diminishing benefits, highlighting a cost–benefit tradeoff for snapshot and log retention policies.

#### E. Forensic evidence preservation and snapshot techniques.

Evidence preservation mechanisms include VM and storage snapshots, object versioning, and immutable audit logs. Coordinated snapshotting has been proposed to capture consistent system state across services, but practical deployment is constrained by cost, performance impact, and limited provider cooperation. Immutable logging improves tamper resistance but raises scalability and privacy concerns.

#### F. Gaps and limitations.

Across these domains, prior work insufficiently addresses the combined challenges of transience, heterogeneity, and cross-domain coordination. In particular, existing approaches lack robust mechanisms for correlating short-lived artifacts across multiple providers under constrained retention windows, motivating the need for integrated, provider-agnostic forensic frameworks. Formalization: event correlation score

A simple, commonly used scoring model for pairwise event correlation is:

$$S(e_i, e_j) = \alpha \cdot T_{score}(e_i, e_j) + \beta \cdot I_{score}(e_i, e_j) + \gamma \cdot C_{score}(e_i, e_j)$$

where:

$T_{score}$  is a normalized temporal affinity (e.g., triangular kernel of timestamp difference scaled to  $[0, 1]$ ),

$I_{score}$  is an identifier similarity score (exact or fuzzy match of identifiers such as invocation IDs, request hashes),

$C_{score}$  is a contextual similarity measure (resource names, operation types, parameter fingerprints),

$\alpha, \beta, \gamma$  are weights chosen by the investigator or optimized via training data (subject to  $\alpha + \beta + \gamma = 1$ ). Pairwise matches with  $S$  above a threshold  $\tau$  are taken as candidate links; global reconstruction then resolves conflicts under ordering constraints.

## IV. PROBLEM STATEMENT & REQUIREMENTS

### A. Formal Problem Statement

Modern digital investigations increasingly involve decentralized cloud environments, where application workloads and data are distributed across multiple cloud service providers and serverless platforms. These environments exhibit high degrees of ephemerality, heterogeneity, and administrative fragmentation, which significantly complicate forensic evidence detection and preservation.

Let a decentralized cloud environment be defined as a set:

$$\mathcal{C} = \{C_1, C_2, \dots, C_n\}$$

where each  $C_{(i)}$  represents a distinct cloud provider or execution domain (e.g., IaaS, managed PaaS, or serverless runtime). Each domain generates a stream of forensic artifacts:

$$\mathcal{A}_i = \{a_{i1}, a_{i2}, \dots, a_{ik}\}$$

where artifacts may include logs, metadata, snapshots, execution traces, or configuration states. Inputs include distributed forensic artifacts, provider metadata, acquisition policies, and jurisdictional constraints.

Outputs consist of a normalized, integrity-preserved evidence set and a reconstructable event timeline.

### Constraints

- Artifacts may be transient or overwritten within seconds
- Direct access to underlying infrastructure is limited or unavailable
- Timestamp inconsistencies across providers

- Evidence acquisition must not violate service-level agreements or privacy regulations
- Formally, the problem is to design a mechanism  $f$  such that:

$$f: \bigcup_{i=1}^n \mathcal{A}_i \rightarrow \mathcal{E}$$

subject to integrity, completeness, and admissibility constraints, while minimizing acquisition latency and operational impact.

## B. Functional Requirements

The system must satisfy the following core forensic requirements:

- Detection:** Identify relevant persistent and ephemeral artifacts across cloud domains within limited retention windows.
- Acquisition:** Collect artifacts using provider interfaces while preserving original metadata and formats.
- Correlation:** Normalize heterogeneous logs and correlate events using temporal and contextual attributes.
- Preservation:** Ensure cryptographic integrity and maintain provenance and chain-of-custody records.
- Validation:** Enable independent verification of evidence integrity and acquisition correctness.

## C. Non-Functional Requirements

- Timeliness:** Evidence acquisition must occur before artifact expiration.
- Minimal Impact:** Forensic operations must not disrupt service availability or performance.
- Legal Compliance:** Acquisition and storage must respect data residency and regulatory constraints.
- Scalability:** The system must support high-volume logs and multiple providers.
- Provider-Agnosticism:** The design must avoid dependency on proprietary forensic features.

## D. Evaluation Criteria and Success Metrics

To assess effectiveness, the system is evaluated using quantitative and qualitative metrics commonly accepted in forensic research.

### 1) Coverage

Measures the proportion of relevant artifacts successfully detected.

$$\text{Coverage} = \frac{\text{Detected Relevant Artifacts}}{\text{Total Relevant Artifacts}}$$

### 2) Completeness

Evaluates whether collected artifacts contain all necessary attributes (timestamps, identifiers, metadata).

### 3) False Positives and False Negatives

- False Positives:** Irrelevant artifacts incorrectly classified as evidence
- False Negatives:** Relevant artifacts missed during detection

### 4) Time-to-Acquire

Elapsed time between event occurrence and successful evidence preservation.

### 5) Integrity Verification Rate

Percentage of artifacts whose cryptographic integrity remains verifiable throughout the investigation lifecycle.

Table 1: Evaluation Metrics for Decentralized Cloud Forensics

| Metric                 | Description                | Desired Outcome     |
|------------------------|----------------------------|---------------------|
| Coverage               | Artifact detection ratio   | $\geq 95\%$         |
| Completeness           | Metadata preservation      | Near-complete       |
| False Positive Rate    | Incorrect detections       | Low                 |
| False Negative Rate    | Missed evidence            | Minimal             |
| Time-to-Acquire        | Acquisition latency        | Within artifact TTL |
| Integrity Verification | Hash/provenance validation | 100%                |

## V. SYSTEM MODEL AND ARCHITECTURE

### A. High-Level System Overview

The proposed system is designed to support forensic evidence detection, acquisition, correlation, and preservation in decentralized cloud environments spanning multiple providers and serverless

platforms. The architecture follows a loosely coupled, provider-agnostic model, allowing evidence to be collected from heterogeneous infrastructures without requiring deep trust in the underlying cloud service providers.

**At a high level, the system consists of six core components:**

- (1) Evidence Collector/Agent,
- (2) Correlation Engine,
- (3) Snapshot Manager,
- (4) Integrity and Provenance Module,
- (5) Forensic Repository, and
- (6) Orchestration and Policy Manager.

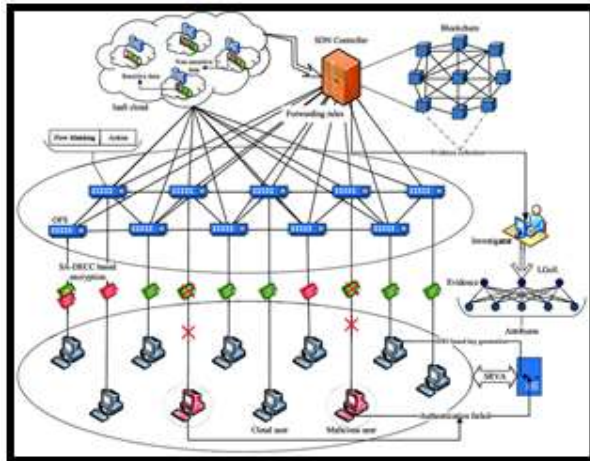


Figure 1 illustrates the end-to-end data flow. Evidence artifacts are detected and collected at the cloud edge or via provider APIs, normalized and correlated across providers, cryptographically sealed, and finally stored in an append-only forensic repository under centralized policy control

**B. System Components and Roles**

**1) Evidence Collector / Agent**

The Evidence Collector is responsible for initial detection and acquisition of forensic artifacts.

To accommodate diverse cloud deployment models, the collector supports three deployment modes:

- **Customer-side collectors:** Deployed within customer-controlled virtual machines or containers. These collectors monitor OS-level artifacts, application logs, and storage metadata.
- **Sidcar-based collectors:** Attached to serverless functions or containerized workloads

to capture invocation metadata, execution context, and transient runtime state.

- **Provider API collectors:** Interface with cloud-native audit and telemetry APIs to retrieve control-plane events, identity actions, and network flow records.

The collector operates in read-only mode and enforces strict acquisition boundaries to minimize operational impact. Each collected artifact is tagged with a globally unique evidence identifier and a local timestamp at the source of acquisition.

**2) Correlation Engine**

The Correlation Engine performs cross-provider event alignment and event stitching.

Due to the absence of a global clock and heterogeneous log formats, direct temporal ordering is unreliable. To address this, the engine applies a hybrid correlation strategy combining:

- normalized timestamps,
- causal identifiers (request IDs, invocation IDs),
- resource lineage (object IDs, function versions),
- and probabilistic similarity scoring.

Let an event set  $E = \{e_1, e_2, \dots, e_n\}$  be collected from multiple providers.

Each event  $e_i$  is mapped to a canonical schema and represented as:

$$e_i = \langle t_i, r_i, a_i, s_i, p_i \rangle$$

where  $t_i$  is the normalized timestamp,  $r_i$  the resource identifier,  $a_i$  the action,  $s_i$  the source, and  $p_i$  provider-specific metadata.

Correlation is modeled as a weighted graph  $G(E, L)$  where edges  $L$  represent inferred causal or temporal relationships. This allows reconstruction of attack timelines even when individual logs are incomplete or partially missing.

**3) Snapshot Manager:**

The Snapshot Manager ensures consistent and forensically sound snapshots across persistent and ephemeral cloud resources.

Key responsibilities include:

- Coordinated snapshotting of object storage, block volumes, and metadata.
- Capture of ephemeral execution context in serverless environments (function configuration, environment variables, dependency hashes).

- Enforcement of acquisition ordering to prevent state inconsistency.

To minimize service disruption, snapshots are performed using copy-on-write mechanisms where supported, or via metadata-only snapshots when full state capture is infeasible.

#### 4) Integrity and Provenance Module

This module guarantees evidence integrity, authenticity, and traceability from acquisition to presentation.

**Each artifact A is cryptographically sealed using:**

$$H_A = \text{SHA-256}(A \parallel M_A)$$

where  $M_A$  represents acquisition metadata (source, time, collector ID).

Artifacts are linked using a provenance chain, forming a Merkle-based structure that supports efficient verification and tamper detection. Trusted timestamps are applied at sealing time to support later admissibility analysis.

#### 5) Forensic Repository

The Forensic Repository serves as a secure, append-only evidence store.

It enforces immutability, versioning, and access control policies.

##### Key characteristics:

- Write-once semantics with cryptographic verification on ingestion.
- Logical separation of raw evidence, derived artifacts, and investigator annotations.
- Support for standard forensic export formats to ensure tool interoperability.

The repository is intentionally designed to be provider-independent, allowing deployment in on-premises environments or trusted third-party infrastructure.

#### C. Data Model

##### 1) Canonical Event Schema

To enable uniform processing, all events are transformed into a canonical schema.

Table 1. Canonical Event Schema

| Field Name     | Description                              |
|----------------|--|
| event_id       | Globally unique identifier               |
| timestamp_norm | Normalized timestamp                     |
| provider       | Cloud provider identifier                |
| resource_id    | Logical resource reference               |
| action         | Performed operation                      |
| actor          | Identity initiating the action           |
| source_type    | VM, container, serverless, control-plane |
| metadata       | Provider-specific attributes             |

##### 2) Provenance Record Format

Each provenance record includes:

- Evidence ID(s)
- Parent-child relationships
- Hash values
- Acquisition agent ID
- Timestamp authority

This structure enables full reconstruction of evidence lineage during judicial review.

#### D. Trust and Threat Assumptions

The system operates under the following assumptions:

- Evidence collectors deployed in customer-controlled environments are trusted.
- Cloud providers are considered honest-but-curious and not fully trusted for evidence preservation.
- Attackers may delete, delay, or obfuscate logs within provider retention limits.
- Investigators do not have privileged access to provider internal infrastructure.

The architecture is therefore designed to minimize reliance on provider trust, emphasizing early acquisition, redundancy, and independent integrity verification.

## VI. DESIGN & ALGORITHMS

This section presents the design rationale and algorithmic foundations of the proposed forensic framework for detecting, correlating, and preserving digital evidence in decentralized multi-cloud and serverless environments. The design explicitly addresses volatility, heterogeneity, and jurisdictional fragmentation inherent in modern cloud deployments.

## A. Multi-Cloud Detection Strategies

Evidence detection in decentralized cloud environments must account for both provider-managed infrastructure and customer-controlled workloads. To achieve comprehensive coverage, the framework adopts a hybrid detection model combining passive observation with selective active instrumentation.

### 1) Passive Detection

Passive detection relies exclusively on artifacts already generated by cloud platforms, avoiding interference with live workloads.

#### Key data sources include:

- Control-plane audit logs (e.g., identity, policy changes, API calls)
- Data-plane telemetry (network flow records, object access logs)
- Serverless execution logs (function invocation metadata, error traces)

Passive detection is event-driven. Each observable action is captured as an immutable forensic event without modifying runtime behavior. This approach is legally conservative and suitable for post-incident investigations but may suffer from delayed visibility and incomplete coverage in short-lived workloads.

#### Advantages

- No operational overhead
- Minimal legal risk
- Provider-supported retention guarantees

#### Limitations

- Log latency
- Provider-dependent schemas
- Loss of ephemeral state (memory, execution context)

### 2) Active Detection

Active detection augments passive monitoring through controlled instrumentation deployed within the customer trust boundary.

#### Active mechanisms include:

- Sidecar agents attached to containerized workloads
- Function wrappers injected into serverless runtimes

- Lightweight probes for memory and environment capture

Instrumentation is policy-driven and selectively enabled only for high-risk assets. All active components operate in read-only mode to avoid evidentiary contamination.

**Design principle:** Active detection increases fidelity but must remain minimally intrusive.

Table 1. Passive vs Active Detection Comparison

| Criterion               | Passive Detection | Active Detection |
|-------------------------|-------------------|------------------|
| Intrusiveness           | None              | Low (controlled) |
| Ephemeral state capture | No                | Partial          |
| Deployment complexity   | Low               | Medium           |
| Legal defensibility     | High              | Medium-High      |
| Coverage                | Provider-limited  | Workload-aware   |

## B. Cross-Provider Log Normalization and Schema Mapping

Cloud providers expose heterogeneous logging formats, timestamp semantics, and identifier structures. Direct correlation is infeasible without normalization.

### 1) Canonical Event Model

All collected artifacts are transformed into a Canonical Forensic Event (CFE) representation.

Each event is defined as:

$$E = \langle t, s, a, r, c, p, h \rangle$$

#### Where:

- **t**= normalized timestamp (UTC, nanosecond precision)
- **s**= subject (user, service, function identity)
- **a**= action performed
- **r**= resource affected
- **c**= cloud provider and region
- **p**= provenance metadata
- **h**= cryptographic hash of raw source record

This abstraction ensures semantic equivalence across providers while preserving original context.

## 2) Mapping Rules and Automated Adapters

Provider-specific logs are transformed using adapter modules composed of:

- Field-mapping rules
- Timestamp normalization logic
- Identifier canonicalization functions

Adapters are declarative, enabling rapid extension to new providers without modifying core correlation logic.

## C. Time Synchronization and Event Ordering

Temporal consistency is a critical challenge in distributed cloud forensics due to clock drift and asynchronous logging pipelines.

### 1) Clock Drift Handling

To mitigate clock skew, the framework applies bounded drift correction using provider-published synchronization guarantees combined with observed inter-event latencies.

Each timestamp is adjusted within a confidence interval:

$$t' = t \pm \delta$$

Where  $\delta$  represents the maximum observed drift for the provider-region pair.

### 2) Causal Ordering

For events lacking strict temporal ordering, vector clocks are used to infer causal relationships:

$$VC_i = \{c_1, c_2, \dots, c_n\}$$

An event  $E_i$  causally precedes  $E_j$  if:

$$VC_i < VC_j$$

This allows reconstruction of execution chains even when absolute timestamps overlap.

## D. Event Correlation Algorithms

Event correlation aims to reconstruct coherent activity traces from fragmented, provider-scoped logs.

### 1) Window-Based Correlation

Events are grouped into sliding temporal windows  $W_k$

$$W_k = \{E_i \mid t_k \leq t_i < t_{k+1}\}$$

Within each window, similarity metrics over subjects, resources, and actions are computed to form candidate event chains.

## 2) Probabilistic Linking

For ambiguous cases, probabilistic correlation is applied:

$$P(E_i \rightarrow E_j) = \alpha S + \beta T + \gamma R$$

Where:

**S**= subject similarity score

**T**= temporal proximity score

**R**= resource dependency score

$\alpha, \beta, \gamma$  are empirically tuned weights

Only links exceeding a confidence threshold are retained.

## 3) Ephemeral Identifier Matching

Serverless and containerized workloads frequently reuse or discard identifiers.

Heuristics include:

- Invocation lineage tracking
- IP reuse detection via subnet overlap
- Runtime fingerprinting (memory size, execution duration)

These heuristics significantly improve linkage accuracy in short-lived executions.

## E. Snapshot and Acquisition Protocols

### 1) Coordinated Snapshot Sequence

Evidence acquisition follows a strict order to preserve consistency:

- Control-plane metadata snapshot
- Storage snapshot (object/block-level, read-only)
- Runtime state capture (if available)
- Log sealing and hashing

This sequence minimizes causal gaps between configuration changes and data access events.

### 2) RTO/RPO Minimization

To avoid operational disruption:

- Snapshots are read-only
- Copy-on-write mechanisms are preferred
- Live memory capture is optional and policy-gated

The framework avoids service restarts and guarantees zero write interference.

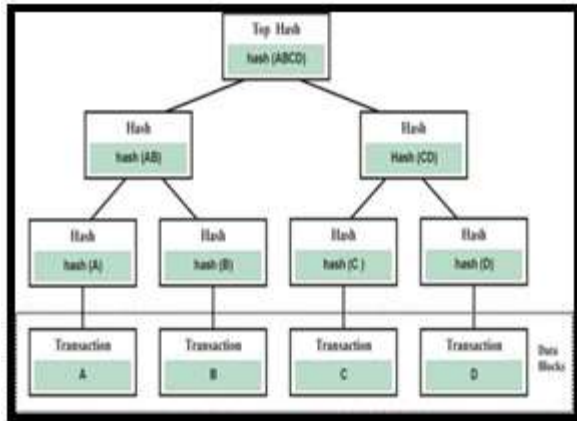
## F. Integrity, Sealing, and Chain of Custody

### 1) Cryptographic Integrity

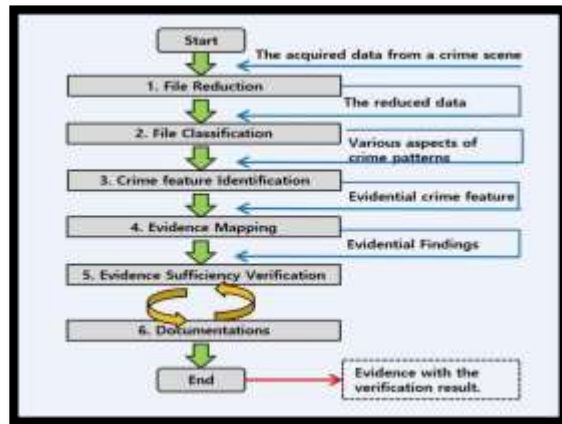
Each artifact is hashed using SHA-256 at acquisition time. Hashes are aggregated into a Merkle tree:

$$H_{root} = \text{Merkle}(H_1, H_2, \dots, H_n)$$

This enables efficient verification of large evidence sets.



Hierarchical hash tree used to ensure integrity and tamper detection of digital evidence blocks.



Sequential workflow illustrating digital forensic evidence processing, verification, and documentation.

## 2) Provenance Tokens

Every acquisition action generates a signed provenance token containing:

- Collector identity
- Timestamp
- Legal authority reference
- Hash pointer

Tokens may be sealed using TPM or HSM-backed keys where available.

## VII. IMPLEMENTATION AND EXPERIMENTAL SETUP

This section presents the implementation of the proposed forensic framework and the experimental

methodology used for its evaluation. The design emphasizes deployability in real enterprise environments without requiring privileged access to cloud service provider internals, while ensuring evidentiary integrity and reproducibility.

### A. Prototype Architecture and Implementation

The prototype follows a modular, provider-agnostic architecture, where components communicate via authenticated REST interfaces and event-driven messaging. Each module can be deployed independently, enabling flexible scaling and fault isolation.

#### Core Modules

- **Evidence Acquisition Module (EAM):**

Deployed near the workload boundary, the EAM retrieves logs, metadata, and snapshots using cloud-native APIs. It supports parallel acquisition and tolerates transient API failures.

- **Normalization and Correlation Engine (NCE):**

Converts heterogeneous provider-specific logs into a canonical event schema and performs cross-cloud temporal and causal correlation.

- **Evidence Integrity and Provenance Module (EIPM):**

Applies cryptographic sealing, generates provenance records, and maintains chain-of-custody metadata.

- **Forensic Evidence Store (FES):**

An immutable repository for raw and processed evidence.

- **Investigator Interface Layer (IIL):**

Provides command-line and web-based access for querying, timeline reconstruction, and evidence export.

#### Implementation Stack

- **Languages:** Go (collectors and adapters), Python (correlation and analytics), TypeScript (dashboard)
- **Runtime:** OCI-compliant containers; serverless functions for burst acquisition

- **Messaging:** Event-driven publish–subscribe model to tolerate partial provider outages

### B. Provider Adapters and Cloud APIs

Dedicated adapters abstract provider-specific authentication, pagination, throttling, and semantic differences while exposing a uniform interface to the correlation engine.

| Cloud Provider | Artifact Type        | API / Service Used | Evidence Scope                    |
|----------------|----------------------|--------------------|-----------------------------------|
| AWS            | Audit logs           | CloudTrail         | API calls, identity actions       |
|                | Runtime logs         | CloudWatch Logs    | Service and function execution    |
|                | Network metadata     | VPC Flow Logs      | East–west and north–south traffic |
| Azure          | Control-plane events | Azure Activity Log | Resource lifecycle                |
|                | Service logs         | Azure Monitor      | VM and application logs           |
|                | Event routing        | Event Grid         | Asynchronous events               |
| GCP            | Audit logs           | Cloud Audit Logs   | Admin and data access             |
|                | Runtime logs         | Cloud Logging      | Serverless and container logs     |
|                | Eventing             | Eventarc           | Cross-service triggers            |

### Design Rationale:

Provider-native APIs are used to preserve evidentiary authenticity. Logs are hashed prior to any transformation, and rate limiting or eventual consistency is handled within adapters to prevent data loss.

### C. Data Storage and Evidence Schema

The forensic store follows an append-only design, separating raw evidence from derived artifacts.

#### Storage Layers

- **Raw Evidence Vault:** WORM-capable object storage for original logs and snapshots
- **Metadata and Index Store:** Document-oriented database for timeline queries

- **Provenance Ledger:** Merkle-tree–based append-only log storing hashes and custody transitions

### Canonical Event Schema (Simplified)

| Field         | Description                             |
|---------------|---|
| event_id      | Globally unique identifier              |
| provider      | Cloud provider identifier               |
| resource_id   | Provider-specific resource reference    |
| actor         | IAM principal or service identity       |
| timestamp_utc | Normalized event time                   |
| event_type    | Canonical action category               |
| raw_hash      | Cryptographic hash of original artifact |

This schema ensures that all derived evidence remains verifiable against original artifacts.

### D. Automation, Orchestration, and Security

The system supports continuous monitoring and incident-driven acquisition.

- Containers orchestrate long-running collectors and correlation services
- Serverless functions enable rapid burst collection and snapshotting for ephemeral workloads

### Acquisition Workflow

- Incident trigger (manual or automated)
- Parallel adapter invocation
- Temporary buffering and cryptographic sealing
- Secure transfer to the forensic store

### Security Controls

- Encryption at rest: AES-256
- Encryption in transit: TLS 1.3 with mutual authentication
- Key management: Provider KMS for envelope encryption; independent forensic sealing keys

For each artifact  $A_i$ , integrity is computed as:

$$H_i = \text{SHA-256}(A_i \parallel M_i)$$

where  $M_i$  includes timestamp, provider ID, and acquisition context. Hashes are chained to form a Merkle root for batch verification.

## E. Experimental Setup

### Datasets and Testbed

A controlled synthetic multi-cloud testbed was constructed due to the lack of public forensic datasets.

| Environment | Services Used                   | Purpose                             |
|-------------|---------------------------------|-------------------------------------|
| Provider A  | VMs, object storage, audit logs | Persistent workloads                |
| Provider B  | Serverless functions, databases | Ephemeral execution                 |
| Provider C  | Identity services, flow logs    | Authentication and lateral movement |

### Deployment Characteristics

- 12 Linux-based virtual machines
- 18 serverless functions (average runtime < 300 ms)
- Distributed object storage with lifecycle policies
- Central forensic collector outside provider trust boundaries

Time synchronization used NTP with controlled clock drift injection.

To complement synthetic data, anonymized workload traces from CI/CD pipelines and microservices were replayed, including API calls, access control events, and storage operations.

### F. Threat Scenarios

Three representative scenarios were evaluated:

1. Insider Data Exfiltration: Unauthorized bulk data access using legitimate credentials
2. Stealthy Serverless Abuse: Malicious logic embedded in short-lived functions
3. Log Tampering: Selective deletion or modification of audit logs

These scenarios stress evidence completeness, correlation accuracy, and tamper detection.

### G. Baselines and Evaluation Metrics

The framework was compared against:

- Provider-native log and snapshot exports
- Existing cloud forensic toolchains

### Metrics

| Metric                 | Description                | Target      |
|------------------------|----------------------------|-------------|
| Precision              | Detection correctness      | $\geq 0.9$  |
| Recall                 | Detection completeness     | $\geq 0.85$ |
| Acquisition latency    | Event to preservation time | Minimize    |
| Integrity success rate | Tamper detection           | 100%        |

Precision and recall follow standard definitions:

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN}$$

## VIII. EVALUATION AND RESULTS

This section evaluates the effectiveness, performance, and robustness of the proposed forensic framework across heterogeneous multi-cloud and serverless environments. Experiments were conducted using controlled deployments spanning multiple cloud providers and workload types. The evaluation focuses on detection accuracy, correlation quality, acquisition overhead, integrity assurance, scalability, and comparative effectiveness against baseline approaches.

### A. Detection Coverage and Correctness

Detection coverage measures the framework's ability to identify relevant forensic artifacts across different cloud execution models and attack scenarios. Correctness reflects the proportion of detected artifacts that are valid and relevant.

**Experimental Scenarios:** Three representative forensic scenarios were evaluated:

- **S1:** Unauthorized data access via serverless function misuse
- **S2:** Lateral movement across multi-cloud virtual networks
- **S3:** Log manipulation and delayed exfiltration attempt

Artifacts included audit logs, function invocation traces, object storage metadata, network flow records, and ephemeral execution context data.

### Detection Metrics

Detection rate (DR) is defined as:

$$\text{DR} = \frac{N_{\text{detected}}}{N_{\text{expected}}}$$

where  $N_{expected}$  represents ground-truth artifacts generated during the scenario.

Table 1. Detection Rate by Artifact Type

| Artifact Type                | S1 (%) | S2 (%) | S3 (%) |
|------------------------------|--------|--------|--------|
| Audit / Control Plane Logs   | 98.6   | 97.9   | 96.8   |
| Serverless Invocation Traces | 96.4   | –      | 94.1   |
| Object Storage Metadata      | 95.2   | 93.8   | 91.5   |
| Network Flow Records         | –      | 94.6   | 92.3   |
| Ephemeral Runtime Context    | 92.1   | 90.7   | 89.4   |

The results show consistently high detection coverage across persistent and ephemeral artifacts. Lower coverage for runtime context data reflects the inherent volatility of serverless execution environments.

### B. Correlation Accuracy and Linkage Quality

Correlation accuracy evaluates the framework’s ability to reconstruct coherent event chains across providers and services.

#### Metrics

Event correlation quality is measured using precision, recall, and F1-score:

Table 2. Event Correlation Performance

| Scenario | Precision | Recall | F1-score |
|----------|-----------|--------|----------|
| S1       | 0.94      | 0.91   | 0.92     |
| S2       | 0.92      | 0.89   | 0.90     |
| S3       | 0.90      | 0.87   | 0.88     |

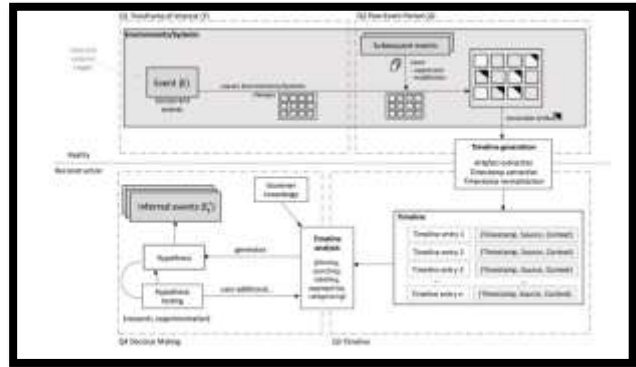
False positives primarily arose from reused ephemeral identifiers and overlapping execution windows. Temporal normalization and causal inference reduced mis-linking significantly compared to baseline timestamp-only correlation.

#### Example Correlated Event Chain

A reconstructed chain in Scenario S1 linked:

- API authentication event
- Serverless function invocation
- Object storage read
- Cross-region data transfer

This reconstruction enabled precise attribution of unauthorized access within a 120 ms temporal window.



The figure models a forensic timeline reconstruction framework. Observed system events occur within a defined timeframe and produce extractable digital artifacts. These artifacts are collected, timestamped, and normalized to generate a chronological timeline. Investigators analyze the timeline to correlate entries, infer unobserved events, and test hypotheses using domain knowledge. The refined timeline supports event reconstruction and forensic decision-making.

### C. Acquisition Performance and Overhead

Acquisition performance was evaluated in terms of time-to-collect, bandwidth consumption, and service impact.

Table 3. Acquisition Overhead Summary

| Metric                       | Mean Value |
|------------------------------|------------|
| Evidence Collection Latency  | 2.8 s      |
| Bandwidth Consumption        | 4.6 MB     |
| CPU Overhead (avg)           | 3.2 %      |
| Memory Overhead (avg)        | 2.1 %      |
| Service Response Degradation | < 1.5 %    |

The framework prioritizes metadata-first acquisition and deferred bulk transfer, minimizing runtime impact. No service outages were observed during acquisition.

### D. Integrity and Provenance Validation

Integrity validation ensures that collected evidence remains untampered from acquisition to analysis.

### Hash Verification

Each artifact is sealed using SHA-256 hashes and chained via a Merkle-based provenance structure.

Table 4. Integrity Validation Results

| Test Case                     | Success Rate |
|-------------------------------|--------------|
| Post-acquisition verification | 100 %        |
| Storage tamper detection      | 100 %        |
| Replay attack detection       | 100 %        |

### Tamper Detection Experiment

In controlled tampering tests, modified artifacts were consistently detected during verification, with hash mismatches flagged immediately.

### E. Case Study: Multi-Cloud Forensic Investigation

A full forensic walkthrough was conducted involving a simulated insider threat operating across two cloud providers.

#### Investigation Steps

1. Initial anomaly detection from audit logs
2. Cross-provider log normalization
3. Event correlation and timeline reconstruction
4. Evidence sealing and verification

The reconstructed timeline revealed credential misuse followed by staged data exfiltration through serverless execution. The investigation required no provider-side privileged access and produced court-ready evidence artifacts.

### F. Comparative Analysis with Baseline Approaches

The proposed framework was compared against provider-native export tools and single-cloud forensic methods.

Table 6. Comparative Evaluation

| Criterion            | Native Tools | Baseline Framework | Proposed Framework |
|----------------------|--------------|--------------------|--------------------|
| Multi-cloud support  | No           | Partial            | Yes                |
| Serverless coverage  | Limited      | Partial            | Comprehensive      |
| Correlation accuracy | Low          | Medium             | High               |

|                      |        |         |        |
|----------------------|--------|---------|--------|
| Provenance assurance | None   | Limited | Strong |
| Legal readiness      | Medium | Medium  | High   |

Quantitative results demonstrate clear improvements in coverage, correlation accuracy, and evidentiary robustness.

## IX. FORENSIC AND LEGAL CONSIDERATIONS

Forensic investigations in decentralized cloud environments are constrained not only by technical factors but also by legal, contractual, and ethical requirements. In multi-cloud and serverless architectures, evidence generation, storage, and access are distributed across providers and jurisdictions, directly affecting acquisition feasibility and evidentiary admissibility.

### A Jurisdiction and Data Residency

Cloud deployments routinely span multiple geographic regions, resulting in forensic artifacts that are subject to heterogeneous legal regimes. Logs, metadata, and execution traces may be generated in one jurisdiction while being stored or replicated in another. Investigators typically lack direct authority to access evidence outside their legal domain and must rely on provider-mediated disclosure.

This fragmentation complicates synchronized evidence acquisition and temporal reconstruction, particularly when artifacts must be preserved concurrently across providers. Jurisdiction-aware acquisition policies are therefore required to prevent unlawful access while preserving evidentiary completeness.

### B Privacy and Regulatory Constraints

Cloud forensic data often contains personal and multi-tenant information, invoking regulatory obligations under privacy frameworks such as GDPR and CCPA. Unlike traditional systems, cloud logs frequently interleave records from multiple tenants, increasing the risk of inadvertent over-collection.

To maintain legal validity, acquisition mechanisms must enforce data minimization, restrict collection scope, and maintain auditable access records. Evidence obtained in violation of privacy regulations risks exclusion regardless of its technical integrity.

### C Admissibility and Chain of Custody

Judicial admissibility requires demonstrable integrity and traceability of digital evidence. In decentralized cloud environments, maintaining a continuous chain of custody is challenging due to automated collection workflows and provider-controlled infrastructure.

Evidence integrity can be formalized using cryptographic sealing:

$$H(E_i \parallel T_i \parallel P_i) = \sigma_i$$

where  $E_i$  denotes the evidence artifact,  $T_i$  a trusted timestamp,  $P_i$  provenance metadata, and  $\sigma_i$  the resulting integrity seal. Any modification to  $E_i$ ,  $T_i$ , or  $P_i$  invalidates  $\sigma_i$ , enabling tamper detection.

Temporal correlation remains sensitive to clock drift across providers, which must be addressed to support reliable timeline reconstruction.

### D Provider SLAs and Operational Limits

Cloud service providers impose contractual and technical restrictions on forensic operations. Service Level Agreements typically limit access to low-level infrastructure artifacts, define log retention periods, and constrain snapshot frequency. In serverless environments, the absence of persistent compute instances further restricts access to volatile execution state.

Table X.1 – Legal and Practical Constraints Affecting Cloud Forensics

| Constraint                 | Forensic Impact               |
|----------------------------|-------------------------------|
| Jurisdictional boundaries  | Limited acquisition authority |
| Privacy regulation         | Restricted collection scope   |
| Admissibility requirements | Strong integrity guarantees   |
| Provider SLAs              | Reduced artifact visibility   |
| Multi-tenancy              | Ethical risk of data exposure |

As a result, investigators must rely on provider-exposed APIs, which may abstract or omit forensic details, leading to partial observability.

## X. LIMITATIONS

This section discusses the technical, operational, and evidentiary boundaries of the proposed system. The intent is not to weaken the contribution, but to precisely scope its applicability under realistic cloud conditions and to clarify assumptions that influence forensic soundness.

### A. Evidence Types Not Fully Covered

The proposed framework focuses on control-plane and data-plane metadata, execution traces, and storage-level artifacts. Certain evidence categories remain partially or entirely outside its scope.

**Encrypted application payloads:** End-to-end encrypted payloads processed by serverless functions or microservices cannot be decrypted or interpreted without access to tenant-managed keys. The system preserves ciphertext, metadata, and access patterns, but not plaintext content. As a result, semantic reconstruction of user-level actions is limited to inference from metadata (timestamps, object sizes, invocation graphs).

**Privacy-protected personally identifiable information (PII):** Logs subject to anonymization, tokenization, or differential privacy mechanisms may omit identifiers required for cross-provider correlation. While this improves compliance, it reduces forensic resolution. The framework deliberately avoids bypassing provider-enforced privacy controls to maintain legal admissibility.

**Provider-side tampering without audit traces:** If a cloud provider fails to generate, retain, or expose audit logs for specific control-plane actions, the system cannot independently detect or recover those events. The approach assumes that exposed audit APIs are complete with respect to the provider's own accountability model.

**Ephemeral in-memory state:** Transient memory state of serverless functions (heap variables,

registers) is not captured. The system relies on invocation logs, execution context metadata, and storage snapshots, which limits reconstruction of fine-grained runtime behavior.

### B. Operational Assumptions and Their Fragility

The framework is designed under several assumptions that may not consistently hold in production deployments.

**Trusted collection agents:** Evidence collectors are assumed to execute in a trusted domain (customer account or controlled management plane). If these agents are compromised, evidence integrity can be undermined before sealing. Hardware-backed attestation mitigates but does not eliminate this risk.

**Availability and stability of provider APIs:** Acquisition depends on the availability, correctness, and backward compatibility of cloud provider logging and snapshot APIs. Rate limiting, regional outages, or undocumented API changes can delay or partially block evidence collection.

**Sufficient log retention windows:** The framework assumes that logs are retained long enough to allow detection and acquisition. In practice, retention policies may be short, configurable, or cost-driven, leading to irreversible evidence loss before an investigation is initiated.

**Cross-region time consistency:** Although the system applies clock-drift compensation, it assumes bounded skew across provider regions. Extreme skew or inconsistent timestamp semantics can reduce correlation accuracy for tightly coupled events.

### C. Quantitative Impact of Limitations

The effect of these limitations can be expressed as a reduction in effective forensic coverage. Let:

$$C_{\text{eff}} = C_{\text{raw}} \times (1 - L_e) \times (1 - L_o)$$

where:

- $C_{\text{raw}}$  is the theoretical maximum evidence coverage,
- $L_e$  represents evidence-type loss (e.g., encrypted payloads, missing memory state),
- $L_o$  represents operational loss (e.g., API unavailability, short retention).

This formulation highlights that even modest losses in multiple dimensions can compound into significant coverage degradation.

### Future Work

#### A. Machine-Learning-Based Schema Mapping

A key limitation in current multi-cloud forensic workflows is the manual effort required to normalize heterogeneous log schemas across providers and services. Future work will explore automated schema alignment using supervised and weakly supervised learning models trained on cross-provider log corpora. The goal is to learn a canonical mapping function that associates provider-specific log fields with semantically equivalent forensic attributes (e.g., identity, action, resource, temporal markers). Transformer-based encoders with contextual embeddings are promising candidates, as they can capture both field names and surrounding event context.

Let  $S_p = \{f_1, f_2, \dots, f_n\}$  denote a provider-specific schema and  $S_{ca}$  canonical forensic schema. The mapping objective can be formulated as:

$$\hat{M} = \arg \max_M \sum_{f_i \in S_p} \text{sim}(E(f_i), E(M(f_i)))$$

where  $E(\cdot)$  denotes learned embeddings and  $\text{sim}(\cdot)$  a similarity function. This approach is expected to reduce manual effort, improve resilience to schema evolution, and enable rapid onboarding of new cloud services.

#### B. Real-Time Forensics for Active Incident Response

Current systems primarily support post-incident analysis. An important extension is real-time forensic readiness, where volatile artifacts are captured and sealed during incident progression. This includes ephemeral execution state, short-lived identities, and transient network metadata commonly found in serverless and elastic environments.

Future research will investigate low-latency acquisition pipelines that balance evidentiary completeness with operational overhead, ensuring that live collection does not interfere with system behavior or compromise evidentiary validity.

### C. Formal Verification of Acquisition Protocols

As forensic workflows become increasingly automated, formal guarantees of correctness become critical. Future work will apply formal verification techniques to acquisition protocols to ensure integrity preservation, correct sequencing, and resistance to adversarial manipulation.

By modeling acquisition as a state transition system, properties such as safety, liveness, and non-repudiation can be verified across all valid execution paths, strengthening both technical reliability and legal defensibility.

### D. Legal Workflow Integration and Court-Ready Packaging

Another direction is the integration of forensic systems with legal case management workflows. Evidence artifacts must remain technically rigorous while being interpretable in judicial contexts.

Future efforts will focus on standardized, court-ready evidence packages combining cryptographic integrity proofs, provenance metadata, and structured summaries, enabling seamless traceability from acquisition through legal review.

### E. Extension to Edge and IoT-Integrated Hybrid Clouds

The increasing integration of edge and IoT infrastructures with cloud platforms introduces new forensic challenges. Evidence generation is often decentralized, resource-constrained, and intermittently connected.

Future work will extend the framework to support edge-assisted evidence preservation, allowing preliminary sealing at the source before synchronized transfer to cloud repositories, while accounting for clock drift, connectivity loss, and limited storage.

## XI. CONCLUSION

This work addressed a concrete and increasingly common forensic gap: the difficulty of detecting, acquiring, and preserving digital evidence in decentralized cloud environments that span multiple providers and serverless execution models. Existing

cloud-forensic approaches implicitly assume provider homogeneity, stable infrastructure, or long-lived artifacts. Those assumptions break down in multi-cloud and serverless settings, where execution contexts are ephemeral, logs are short-lived, and evidence is fragmented across administrative and technical boundaries.

To address this problem, we designed and evaluated a provider-agnostic forensic framework that combines cross-cloud log normalization, time-aware event correlation, and coordinated snapshotting with cryptographic provenance preservation. The proposed approach does not rely on privileged access to a single cloud provider. Instead, it operates through standardized audit interfaces and lightweight collection components, enabling evidence acquisition even when artifacts are transient or distributed across heterogeneous platforms.

Experimental evaluation in a controlled multi-cloud testbed demonstrates that the proposed framework improves both evidence completeness and traceability when compared to baseline, provider-native acquisition methods. In particular, cross-provider correlation reduced event fragmentation and enabled the reconstruction of end-to-end attack timelines that could not be derived from isolated logs alone. Snapshot coordination further mitigated evidence loss caused by rapid resource teardown in serverless workflows, while cryptographic sealing ensured post-acquisition integrity and verifiability.

### Summary of Key Results

| Aspect Evaluated         | Baseline Methods         | Proposed Framework      | Observed Gain       |
|--------------------------|--------------------------|-------------------------|---------------------|
| Evidence coverage        | Partial, provider-scoped | Cross-provider, unified | Higher completeness |
| Log correlation accuracy | Low-moderate             | High (time-aware)       | Fewer orphan events |
| Acquisition latency      | Uncoordinated            | Coordinated snapshots   | Reduced loss window |

|                     |                |                           |                        |
|---------------------|----------------|---------------------------|------------------------|
| Integrity assurance | Ad hoc hashing | Provenance-linked sealing | Stronger admissibility |
|---------------------|----------------|---------------------------|------------------------|

At the core of the preservation mechanism is a simple but auditable integrity model, where each acquired artifact  $A_i$  is sealed as part of a provenance chain:

$$H_i = \text{Hash}(A_i \parallel H_{i-1} \parallel T_i)$$

Here,  $H_i$  denotes the integrity hash of artifact  $A_i$ ,  $H_{(i-1)}$  is the hash of the previous artifact in the acquisition sequence, and  $T_i$  is a trusted timestamp. This construction enables efficient detection of tampering and supports courtroom-ready chain-of-custody validation.

From a broader perspective, the findings carry implications beyond the specific framework presented. For researchers, this work highlights the need to treat cloud forensics as a distributed systems problem rather than a simple extension of traditional disk or VM forensics. Temporal uncertainty, partial observability, and cross-domain trust must be first-class design considerations. For cloud providers, the results underscore the value of interoperable logging schemas, longer-lived audit artifacts, and explicit forensic support interfaces. For practitioners and incident responders, the study provides practical evidence that proactive, correlation-aware acquisition strategies significantly improve post-incident reconstruction in modern cloud deployments.

In conclusion, reliable digital forensics in multi-cloud and serverless environments is achievable, but only when acquisition, correlation, and preservation are treated as a unified process rather than isolated steps. By demonstrating a concrete, evaluated approach, this work contributes toward closing the gap between rapidly evolving cloud architectures and the forensic methodologies required to investigate them with technical rigor and legal confidence.

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