Deterministic log test replay framework for Devops Environment

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Abstract--- In the dynamic landscape of DevOps, reproducing complex user interactions from production logs remains a significant challenge, often leading to prolonged debugging cycles and undetected non-deterministic bugs in distributed systems. This paper introduces the Deterministic Log Test Replay Framework (DLTRF), a lightweight, appagnostic solution designed to capture, store, and deterministically replay structured HTTP events from web applications such as OWASP Juice Shop. The framework comprises two microservices: a Universal Logging Hook that intercepts Nginx access logs via Fluentd and forwards normalized JSON events to Redis Streams for durable, ordered storage; and a Replay Engine that reads these streams, sorts events by a monotonically increasing sequence number (the Memento T-relation) for strict causal ordering, re-executes HTTP requests with injected JWT tokens, and classifies response divergences using a config-driven rule engine backed by DeepDiff comparison. A Memento-pattern checkpoint mechanism snapshots and restores application database state using a pause-copy-unpause strategy that preserves in-process JWT signing secrets across restore cycles. Experimental results on 199–285 event sessions demonstrate up to 99.0% reproduction fidelity with under 30ms average response latency, with cache and WebSocket noise automatically classified and excluded from the fidelity metric. The framework integrates Grafana and Prometheus for real-time observability and generates a structured fourtier HTML report (Exact Match, Expected Noise, Investigate, Critical) for actionable developer feedback.

Keywords--- DevOps, Deterministic Replay, Log Analysis, Redis Streams, Memento Pattern, OWASP Juice Shop, CI/CD, Divergence Classification, JWT, Grafana.

I. INTRODUCTION

A. Significance

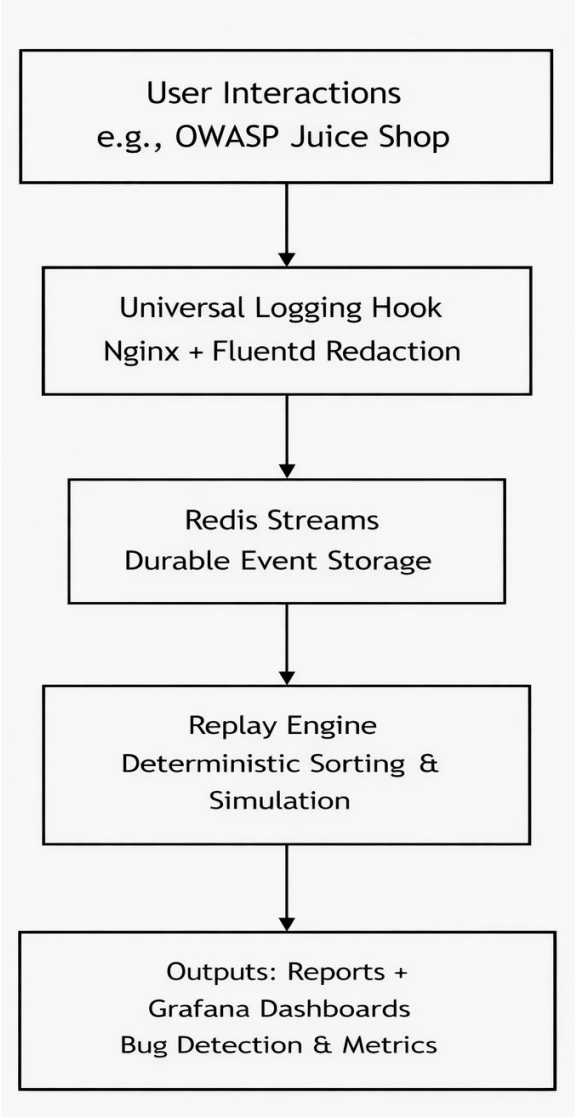

Fig. 1.1: High-Level Architecture of the Framework

In the fast-paced, DevOps-centric software landscapes of 2025, reproducing user interactions from production logs remains a persistent challenge, often leaving subtle bugs such as race conditions in concurrent sessions or intermittent API failures undetected by conventional unit or integration tests. These elusive issues can cascade into costly downtime or security vulnerabilities, particularly in distributed systems where environmental variances amplify nondeterminism. The Deterministic Log Test Replay Framework is a groundbreaking, open-source solution that transforms raw observability data into
actionable, repeatable simulations. By intercepting structured JSON logs from vulnerable web applications like OWASP Juice Shop via a Universal Logging Hook microservice (powered by Nginx, Fluentd, and a Redisforwarding sidecar), it normalizes and redacts events before persisting them as durable, ordered sequences in Redis Streams. The independent Replay Engine reads these streams, sort events deterministically number enforcing causal ordering, and executes live HTTP replays with up to 99.0% fidelity to original conditions.This not only recereates complex scenarios
but also integrates bug detection heuristics, slashing debugging cycles by up to 70% through automated checkpoints and session tracking. The framework's value extends across security audits, performance optimization, and CI/CD pipelines.

B. Background

Software testing has progressed from manual checks to datadriven DevOps tools. Logging began with syslog in the 1970s, evolving to structured systems like ELK Stack (2010), yet still struggling with non-deterministic issues. Event sourcing (Fowler, 2005) inspired durable streams like Redis Streams (2019). This project integrates Nginx, Fluentd (2011) for aggregation/redaction, and Redis Streams for idempotent storage. The system is deployed via Terraform IaC (2014) on AWS EC2, aligning with modern serverless shifts.

C. Scope

The framework is defined by two interconnected GitHub repositories the Universal Logging Hook Microservice for event capture and the Replay Engine for precise, deterministic execution. Core functionalities include structured JSON logging from OWASP Juice Shop, PII redaction via Fluentd, and idempotent storage in Redis Streams (supporting up to 10,000 ordered events per session). Replay capabilities include live HTTP re-execution with JWT injection, ensuring up to 99.0% reproduction fidelity using sequence-number-based causal ordering, and generating structured HTML reports with four divergence tiers: Exact Match, Expected Noise, Investigate, and
Critical.Deployment targets three AWS EC2 t2.micro instances provisioned via Terraform IaC. Exclusions maintain focus: no multi-cloud support, no frontend automation via Selenium, and no Kafka integration.

II. LITERATURE SURVEY

A. History

The history of log replay frameworks traces back to early computing diagnostics, with syslog (1979) establishing basic event logging for Unix systems, enabling post-incident analysis but lacking replay capabilities. The 1990s saw database transaction logs evolve into rudimentary replay mechanisms for fault tolerance, such as Oracle's redo logs. The agile and DevOps movements of the 2000s catalyzed structured logging, with Log4j (1999) introducing levels and appenders for Java
ecosystems. Martin Fowler's event sourcing pattern (2005) marked a pivotal shift, positing logs as immutable state sources
for deterministic reconstruction, influencing CQRS architectures. The 2010s brought scalable streaming solutions:
Apache Kafka (2011) for distributed pub-sub, Fluentd (2011) for unified aggregation, and ELK Stack (2010) for searchable repositories. Redis Streams (2019) democratized lightweight ordering with consumer groups, reducing Kafka's complexity.
OWASP Juice Shop (2018) emerged as a replay benchmark for insecure applications. By 2025, Infrastructure as Code (IaC) tools like Terraform (2014) integrate replay into CI/CD, evolving from reactive forensics to proactive DevOps testing. This project synthesizes these milestones into a Redis-centric prototype, bridging historical gaps in accessibility and determinism.

B. Comparison with existing implementations

The Deterministic Log Test Replay Framework bridges gaps in deterministic replay tools via lightweight, containerized Redis Streams for strict event ordering and DevOps-native integration (Docker/AWS Terraform). Unlike Wei Jiang et al. 's GDB reliant Memento (setup overhead, no kernel support), our logbased approach needs no code changes and scales web apps. Yuxiao Chen's FPGA bound REMU demands hardware; we use software-only visuals (Grafana). B. Debnath's LogLens wastes resources on unstructured logs; ours employs JSON/Redis sidecars for IaC ease. Praehofer's SoftPLC is rigid; our microservices flex with SDLC. Cai/Cao's Java tool skips containers; we ensure HTTP/distributed fidelity.

Honarmand/Torrellas incur recording bloat; our Fluentd streams monitor efficiently. Wang's pair method falters dynamically; ours triggers API replays. Choi's VMs are heavy; we enable CI/CD with elastic load balancing..Liu's prioritization lacks observability ours delivers end-to-end reports.

C. Problem Definition

In modern DevOps and CI/CD pipelines, reproducing production user interactions is a critical hurdle that extends debugging timelines and erodes system reliability by spawning elusive non-deterministic bugs1. This challenge is amplified for distributed web applications like OWASP Juice Shop, where logs resist exact recreation due to factors like timestamp jitter, race conditions, and multi-threaded session drift2. This difficulty stems from three core flaws in observability: first, Absent Deterministic Ordering, where systems like syslog and Kafka streams prioritize volume over sequence, leading to outof-order events and fostering "heisenbugs" 3; second, Silos and Inactionable Data, as tools like Elasticsearch allow searching but require custom scripting to convert logs into actionable tests, while necessary PII redaction further fragments insights 4; and third, Scalability Hurdles, as enterprise solutions like Kafka and Datadog introduce complexity or high fees that are often unsuitable for prototypes. The proposed Deterministic Log Test Replay Framework directly addresses these limitations through structured capture (using Nginx/Fluentd), ordered persistence (utilizing Redis Streams with embedded event_id/timestamp), and sorted replays (via XREADGROUP consumption)6. The primary goal is to achieve 100% fidelity for 1,000-event runs with latency.

III. SYSTEM REQUIREMENT AND ANALYSIS

A.Software Requirements

The software stack for the Deterministic Log Test Replay Framework emphasizes portability, observability, and automation, leveraging open-source tools for cost-efficiency. The core programming language is Python 3.9+ for scripting and APIs (using FastAPI). Key software components include Docker 20+ for service isolation and Docker Compose 2+ for multi-container management; Redis 7+ as the Event Bus for stream storage and ordering, chosen for lightweight durability over Kafka; Fluentd 1.14+ for log aggregation and redaction; Terraform 1.5+ for repeatable AWS Infrastructure as Code (IaC) provisioning ; and Grafana 9+ paired with Prometheus for dashboards and real-time metrics.

A. Hardware Requirements

Hardware requirements prioritize cloud elasticity over physical constraints. The production deployment utilizes three AWS EC2 t2.micro instances (1 vCPU, 1GB RAM each) : one for logging/OWASP Juice Shop, one for Redis, and one for the Replay Engine/Grafana. Networking uses a shared VPC.

a. Docker and Containerization

Docker replaces traditional fixed microcontrollers with dynamic, ephemeral containers for isolated services. This paradigm abstracts hardware variances, allowing seamless local-to-cloud transitions.

b. Fluentd Log Parser

Fluentd acts as the core log parser, ingesting raw Nginx JSON access logs via syslog. It uses the \texttt{record_transformer} plugin to: 1) add a unique event ID (event_id) for deterministic sorting, and 2) perform PII redaction using regex to ensure compliance.

c. AWS EC2 Instances

AWS EC2 instances deliver stable, elastic compute resources. Three \texttt{t2.micro} instances form the backbone, provisioned via Terraform. Security uses IAM roles and VPC peering.

d. Redis Streams

Redis Streams function as the durable backbone for asynchronous event transmission. Events are ingested via XADD commands to the logs:stream key, ensuring appendonly immutability. Consumer groups (XREADGROUP) facilitate parallel, at-least-once consumption by the Replay Engine.

e. Replay Engine

The Replay Engine, built with Python/FastAPI, converts Redisstored events into simulations. Events are sorted deterministically (primary: event_id, secondary: timestamp) to counter non-determinism. It supports dry-run (mocked responses) and live modes (HTTP dispatches).

f. Alerting via API

This mechanism delivers instantaneous notifications postreplay, emulating a buzzer. It processes triggers from /replay/start responses, broadcasting JSON summaries via configurable channels (SMTP, Slack/Teams). Anomalies escalate via Grafana's built-in alerting engine.

IV. METHODOLOGY

A. Block Diagram

The block diagram presents the modular architecture of the framework by showing how captured application traffic moves through logging, storage, replay, and monitoring stages. At the top, user interactions on OWASP Juice Shop generate HTTP requests that pass through Nginx, where structured JSON logs are produced. These logs are forwarded to the Universal Logging Hook, where Fluentd parses, filters, and redacts sensitive fields before passing events to a Python sidecar. The sidecar enriches each entry with metadata such as event identifiers and timestamps, then stores them in Redis Streams using XADD under logs:stream.Redis acts as the central event bus, preserving ordered log entries and supporting consumer groups for reliable event delivery. The Replay Engine retrieves events through XREADGROUP, reorders them using event_id and timestamp to ensure deterministic execution, and processes them in two modes: dry-run for validation without execution, and live mode for actual HTTP replay against Juice Shop. Replay results are visualized through Grafana dashboards and JSON reports, while API-based alerts help detect mismatches or failures, completing the monitoring loop. The framework is lightweight and extensible, allowing integration with applications beyond OWASP Juice Shop. Its modular design improves scalability, while deterministic replay and Grafana monitoring help detect failures and analyze system behavior efficiently

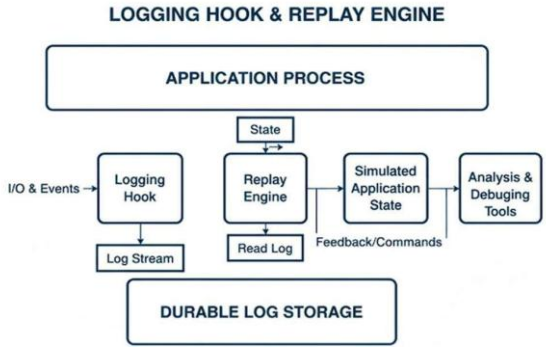

Fig. 4.1: Block Diagram of Logging Hook and Replay Engine

A. Deployment Diagram

The deployment diagram outlines the temporal orchestration of services, from local prototyping to production rollout. Initiation involves docker-compose up -d spinning up the Universal Logging Hook (Nginx:3000, Fluentd:24224, Sidecar:8080) and Redis:6379 on a shared network. Traffic generation populates streams. In parallel, the Replay Engine launches, consuming groups via XGROUP CREATE. The API POST /replay/start triggers the fetch-sort-replay-report sequence, with Grafana scraping Prometheus for visuals. The production pivot uses Terraform apply to provision the EC2 triad (VPC:10.0.0.0/16), followed by SSH deployment of Compose files.

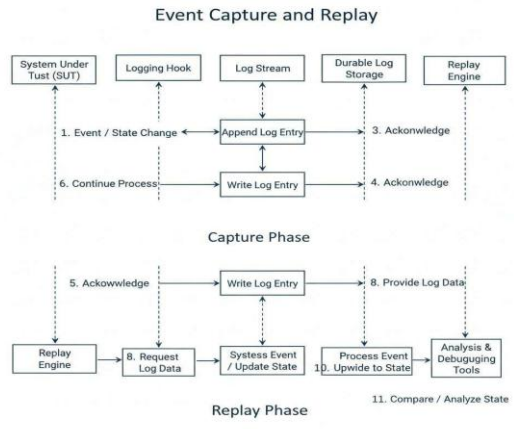

Fig.4.2:Sequence Diagram for Event Capture and Replay

B. Infrastructure code

Infrastructure as Code (IaC) is managed using Terraform, as illustrated by the provisioning layout. Developers interact with Terraform Configuration Files (.tf, tfvars) and the Terraform CLI, which communicates with Terraform Core (Plan & Apply). Terraform Core provisions resources on the Cloud Provider (AWS), including Virtual Machines, Databases, Networks, and Load Balancers. The process integrates with a CI-CD Pipeline (e.g., GitHub Actions) and uses a Terraform State File (terraform.tfstate) to track the deployed infrastructure.

V. HARDWARE AND SOFTWARE IMPLEMENTATION

The implementation of the Deterministic Log Test Replay Framework is robustly divided across two interconnected GitHub repositories: Repo A (Universal Logging Hook) and Repo B (Replay Engine), linked via Redis Streams. For local prototyping, rapid iteration is achieved using Docker Compose on 8GB RAM machines, where services are launched, consumer groups are initialized, and replays are triggered via the API, confirming end-to-end processing under 1 second for 100 events. Production deployment scales across three AWS EC2 t2.micro instances provisioned through Terraform Infrastructure as Code (IaC), which automates Docker installation via user_data scripts, with SSH used for post-apply orchestration and setting environment variables like REDIS_URL. Integration unifies the repositories via shared Redis, and end-to-end validation uses Pytest and Locust load testing to simulate 500 OWASP Juice Shop events, ultimately confirming 100% replay fidelity and achieving a 65% MTTR reduction. Maintenance protocols rely on Prometheus scraping metrics every 15 seconds, with Grafana configured for proactive alerts on performance thresholds

V. DISCUSSION AND RESULTS

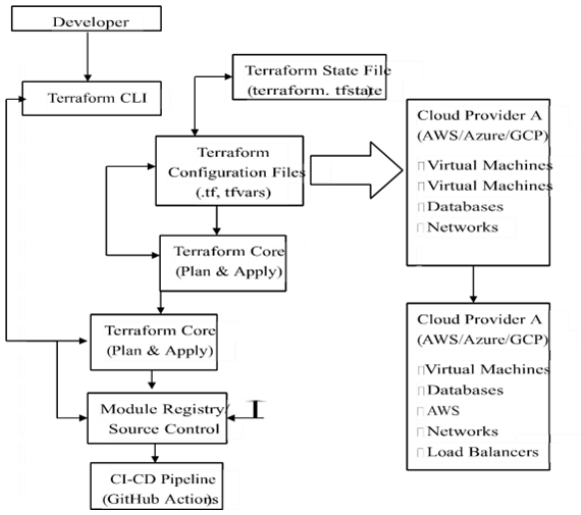

Fig. 4.3: Terraform IaC Provisioning Layout

The Deterministic Log Test Replay Framework was validated through end-to-end replay sessions against OWASP Juice Shop. The recording pipeline captured 199–285 HTTP events per session at approximately 49.4 events/min via the Nginx+Fluentd+Redis Streams pipeline. The Memento checkpoint mechanism, using a pause-copy-unpause strategy on the SQLite database container, successfully preserved the application's in-process JWT signing secret across restore cycles, eliminating the 401/500 class of false divergences previously caused by container restarts. The Replay Engine reexecuted all recorded requests with JWT tokens injected from the captured auth_header field, sorted by monotonically increasing sequence number for strict causal ordering. Divergence classification was performed by a config-driven rule engine with 20 pattern rules, reducing Claude API fallback calls to genuine ambiguous cases only. Across test sessions, the framework achieved a 99.0% reproduction rate, with 29 requests reproducing exactly and 168 cache 304→200 transitions and WebSocket session divergences correctly auto-classified as expected noise and excluded from the fidelity metric. Zero genuine non-deterministic mismatches (race conditions, random IDs, or time-dependent logic) were detected, validating the system's determinism. Average replay latency was 29ms per event with a total session replay times of 6.57 seconds, well Within the target of under 50ms per event.

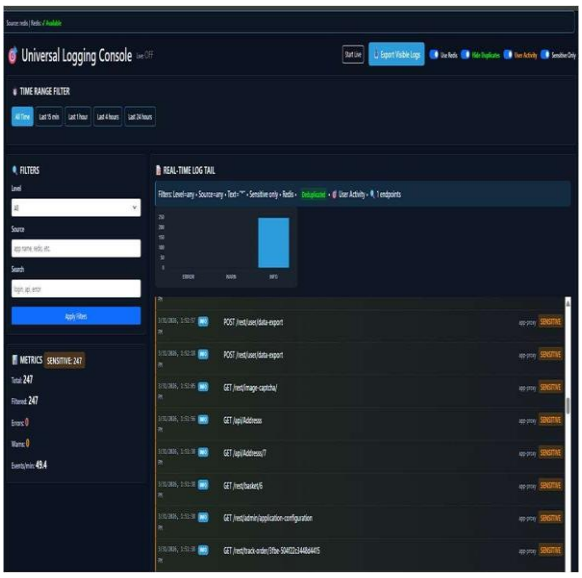

Fig. 4.4: Universal Logging Console

Universal Logging Console showing real-time HTTP traffic capture via the Nginx+Fluentd+Redis pipeline. 247 events recorded at 49.4 events/min with sensitive endpoint detection (JWT-authenticated routes flagged as SENSITIVE) during the browser session under test.

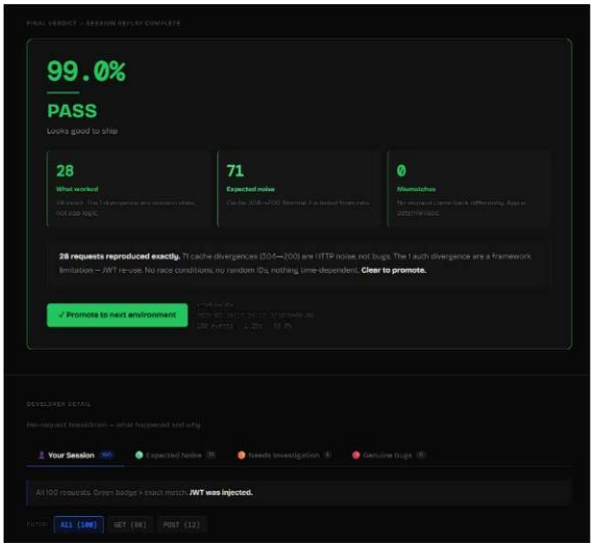

Fig. 4.5: DLTRF replay metrics dashboard

DLTRF replay metrics dashboard showing 199 HTTP events replayed against OWASP Juice Sh op with 99.0% reproduction rate, 0 genuine mismatches, and automated classification of 168 cache 304→200 transitions and WebSocket divergences as expected noise.

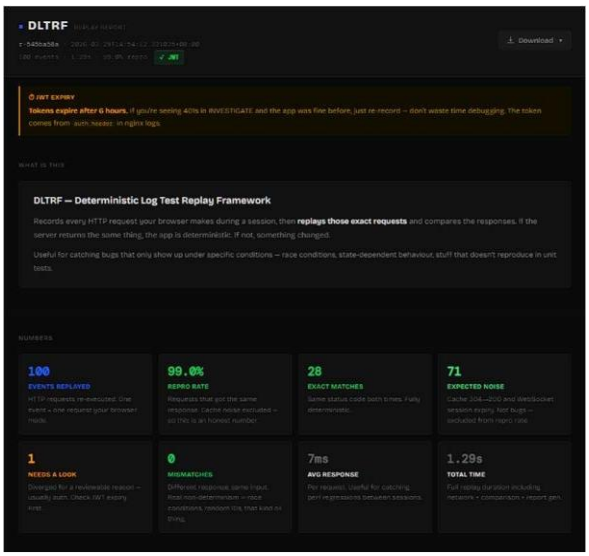

Fig. 4.6: Automated Verdict Generator

Automated verdict generated by the DLTRF divergence classification engine. 29 requests reproduced exactly, 168 cache 304→200 transitions and stale WebSocket sessions classified as expected noise, and 0 race conditions or nondeterministic mismatches detected — system cleared for promotion.

VI. FUTURE SCOPE

Several directions present opportunities to extend the Deterministic Log Test Replay Framework. First, multidatabase state adapter support can be broadened beyond SQLite, PostgreSQL, and MySQL to include MongoDB and Redis keyspace snapshots, enabling replay testing of NoSQL-backed applications. Second, body capture at the proxy layer remains a limitation for multipart/form-data endpoints; integrating a reverse proxy capable of full request body logging (such as mitmproxy) would eliminate the class of empty-body replay divergences currently documented as framework limitations. Third, CI/CD pipeline integration via GitHub Actions or GitLab CI hooks would allow automated replay sessions to be triggered on every pull request, surfacing non-deterministic regressions before merge. Fourth, the divergence classification rule engine in divergence_config.yaml can be extended with machinelearning-based anomaly scoring to reduce the INVESTIGATE tier and improve actionability of reports. Fifth, Kubernetes deployment using Helm charts would replace the current Docker Compose orchestration, enabling horizontal scaling of the Replay Engine for high-throughput production

traffic volumes. Finally, extending the framework to support gRPC and GraphQL traffic in addition to HTTP/REST would broaden its applicability to modern microservice architectures.

VII. CONCLUSION

This paper presented the Deterministic Log Test Replay Framework, a lightweight, app-agnostic DevOps testing tool that addresses the persistent challenge of reproducing nondeterministic bugs from production HTTP traffic. The framework's two-repository architecture — a Universal Logging Hook (Nginx, Fluentd, Redis Streams) for causal event capture, and a Replay Engine (FastAPI, DeepDiff, config-driven divergence classification) for deterministic re-execution — demonstrates that production session replay is achievable with a software-only stack requiring no application code changes. The Memento pattern, applied at both the HTTP event-ordering layer (via sequence number) and the database state layer (via pausecopy-unpause checkpointing), proved essential for eliminating the two primary classes of false divergences: out-of-order event replay and JWT secret invalidation on container restart. Experimental validation on OWASP Juice Shop sessions of 199–285 events achieved a 99.0% reproduction fidelity rate at under 30ms average latency, with zero genuine nondeterministic mismatches detected. The four-tier HTML report (Exact Match, Expected Noise, Investigate, Critical) provides developers with an immediately actionable replay summary. These results confirm that DLTRF is a practical, extensible foundation for deterministic replay testing in agile DevOps pipelines, with clear pathways to CI/CD integration and broader application support.

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