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A Cloud-Native Architecture for Scalable Real-Time Security Telemetry Ingestion and Threat Signal Processing

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Abstract

The explosive growth of distributed cloud apps has resulted in an explosion of security telemetry, posing tremendous challenges for real-time ingestion, processing, and detection of threats. In this paper, we propose a cloud-native architecture of scalable real time security telemetry ingestion and threat signal processing that is equipped to address the challenges associated with high velocity and large volume security data in low latency manner under high availability across all regions. The architecture uses containerized microservices, event-driven messaging and stream–processing frameworks to ingest and process over 5M telemetry events per second with an average end-to-end processing latency of less than 120 ms. We illustrate that the system is capable of scaling out (0-10× workload) while maintaining minimum level of service loss. A distributed data pipeline with >99.99% availability and schema-on-read and adaptive buffering, which executes ingestion 35% more effectively than monolithic log-processing solutions. Near real-time threat signal enrichment and correlation are carried out with rule-based and machine learning supplemented analytics, delivering a 27% increase in the accuracy of detected threats as well as 42% decrease in false positives. In contrast to others, our experimental results in the cloud testbed indicate that by an average of 30% lower operational overhead, and 22% cost-savings can be achieved using dynamic resource allocation. The findings affirm that cloud-native design patterns materially improve scaling, resiliency and agility in contemporary security operations, rendering the architecture suitable for enterprise-wide or multi-cloud environments.

Keywords: Cloud-native security, real-time telemetry ingestion, threat signal processing, scalable security architecture, security analytics

1. Introduction

Cloud computing, microservices and distributed application architectures have revolutionized the way that modern enterprises build, deploy & operate digital systems. Although these paradigms enable scalability, flexibility, cost efficiency unattainable with traditional systems, they have introduced a new set of complicated security issues due to system diversity and heterogeneity, dynamic workloads, and widespread deployment environments [1]. As a consequence, organizations today produce huge amounts of security telemetry - in the form of logs, metrics (basic measurements), traces (data that shows how a request to one service is processed and responded to by other services; it provides vital info on response time, failure rate, and performance bottlenecks), network flows (a precise record of the packets required to reassemble

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traffic), endpoint signals - which need to be ingested and analyzed in real time for actionable threat detection [2].

Traditional SIEM and log management systems were really built for static environments that are local, on premise, and workloads are pretty predictable. These historical systems are poorly suited to deal with the velocity, volume and variety of telemetry generated by cloud-native environments resulting in ingestion bottlenecks, delayed threat detection and high numbers of false positives [3]. Moreover, centralized and monolithic architectures often have insufficient elasticity and fault tolerance to support real-time security operations with large scale [4].

Cloud-native architectural patterns based on microservices, containerization, orchestration and event-driven processing have great potential to address these challenges [5]. Distributed systems and messaging along with stream-processing frameworks allows collecting high-frequency telemetry data continuously through cloud native platforms for near real-time processing. This architecture also enables security systems to horizontally scale, react responsively to workload variations and stay tolerant to failures [6].

Real-time threat signal feed processing is a crucial need for contemporary SOCs. Sophisticated threats, such as zero-day attacks, lateral movement attacks and insider threats, typically take a few seconds or minutes to execute [7]. An increased attack surface and potential impact can result from delays in the ingestion or analysis of telemetry. Accordingly, the inclusion of real time analytics, correlation engines and machine learning aided detection mechanism in the ingestion pipeline has become inevitable for performing proactive security monitoring [8].

Even with these recent improvements, we were drawing blood from a stone to come up with an architecture that's scalable, efficient, and without breaking the bank for ingesting real-time security telemetry. Challenges have to do with coping with heterogeneous data formats, meeting low-latency processing times at bursty workloads, guarantee high availability and maximize the use of resources in multi-clouds [9]. These two competing requirements need to be balanced, in the context of a cloud-native architectural worldview that can strike the right balance between these design patterns and the security-sensitive processing needs.

Against this backdrop, we present a cloud-native blueprint for elastic real-time ingestion of security telemetry and signal processing. The architecture focuses on modular microservices, event-driven pipelines, elasticity of scale and integrated analytics to enable high throughput telemetry stream with lowest possible latency. Through integrating security processing to the cutting-edge cloud-native practices, this work can significantly elevate both detection accuracy and efficiency in practice while ensuring a higher level of system robustness, making it practical for large-scale enterprise and multi-cloud setups.

2. Literature Review

Previous studies of high-throughput security surveillance systems often considered centralized log collection and batch-based analysis, which is suitable for traditional enterprise infrastructures but

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insufficient to cope with dynamic and large-scale distributed clouds. These solutions were often beset with high ingestion latencies, limited scalability, and slow threat detection as a result of the tight integration between the layers for collecting data and analyzing it. Research has shown that centralised architectures quickly become performance bottlenecks as telemetry volume increases, leading to loss of data and incomplete security visibility in deployed solutions [10].

Following studies looked into distributed log aggregation and message-queue-based pipelines to overcome the scalability and fault tolerance bottlenecks. Through separation of producer and consumer, those architectures increased throughput and made possible parallel processing of security events. Nevertheless, many of the work reported adaptation difficulties about message ordering, backpressure handling and consistent schema management in the context of a heterogeneous telemetry source over hybrid/multi-cloud environments. Whilst these systems were able to increase ingestion capacity, real-time threat correlation was still constrained by a lack of capable stream-processing [11].

With the advent of cloud-native computing, researchers starting exploring microservices, containers and orchestrations platforms to develop adaptable security data pipelines. The experiments showed that digestible ingestion services with auto-scaling could significantly decrease processing latency and enhance system tolerance under bursty workloads. However, OWOP and additional inter-service communication overhead presents significant difficulty particularly in large security operations deployment [12].

Real-time stream processing frameworks for security analytics Recent literature highlights the focus of real-time stream processing frameworks in relation to security analytics, allowing continuous correlation, enrichment and anomaly detection. Such systems enable low-latency query processing and stateful analysis, suitable for identifying rapidly-evolving threats. The experimental results demonstrated significant performance improvement on detection latency, but the challenge of balancing accuracy and false positives when dealing with high dimensional and noisy telemetry measurements still existed [13].

Machine learning enabled techniques have found their way into security telemetry processing pipelines to improve the detection and prioritization of threat leads. It was also shown that streaming data with statistical models can improve adaptability to new attack patterns. However, drawbacks such as model drift, explainability and computational cost of real-time inferences within high-throughput scenarios remained a concern 14.

In [7] the authors evaluate cloud and multi-cloud security analytics solutions, considering the required elastic behavior, fault containment and cost awareness for such a solution. They demonstrated that using auto-scaling and serverless objects could decrease the operational cost without loss of performance. Nevertheless, obstacles regarding cross-cloud data transfer, wide ranging latency and the enforcement of policies were highlighted as open issues [15].

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More recent studies [7, 8] recommended end-to-end architectures for security telemetry which combine ingress, processing, storage and visualization into a common pipeline. Such systems enhanced situational awareness for security operations centers, by delivering near real time information. However, assessments also showed that tightly integrated systems often sacrificed flexibility and made it hard to deploy incremental upgrades in ever changing clouds [16].

Roles of replication, checkpointing and recovery to provide high-availability and fault-tolerance security data pipelines were emphasized by several studies to guarantee uninterrupted operation during failures. Although these solutions enhanced system reliability, they also introduced extra communication and storage overhead that might compromise the efficacy of real-time threat detection in overloaded situation [17].

Recent work also demonstrates the applicability of event-driven and serverless architecture for processing of security telemetry data. These methodologies were touted to gain good performance in scaling and less effort put into managing the infrastructure. However, cold start latency and lack of control over execution environment were identified as important limitations for latency-sensitive security applications [18].

Finally, recent literature pointed to the absence of agile architectural blueprints that organically blend cloud-native design patterns and real-time security analytics needs. The literature consistently emphasizes the requirement of scalable, low-latency, and cost-effective designs that are able to manage heterogeneous telemetry, process advanced threat signals, and work across multi-cloud environment with high availability [19], [20].

3. Methodology

The cloud-native security telemetry architecture is developed by constructing the two mainframe of methodology such as architectural foundation design for the target and methodological framework based on which there is evaluation and optimisation of system. This section describes the engineering motivation, mathematical theory and experimental design used to obtain scalable realtime processing of threat signals.

Architecture of the Proposed System

The architecture uses a layered microservice pattern orchestrated by Kubernetes working in concert with event driven communication established via Apache Kafka. The architecture of the system is composed by five main layers: ingestion layer, buffering and routing layer, stream processing layer, enrichment and correlation layer and storage and analytics. Each layer is scalable horizontally, and isolated in faults.

The ingestion layer collects security telemetry from dispersed sources such as endpoint agents, network sensors, cloud service logs, and application monitoring data. Telemetry events are ingested through RESTful APIs and secured message queues, validated and normalized. The ingestion throughput capacity is given in Equation (1):

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$$T_{ingestion} = \sum_{i=1}^{n} \frac{E_i}{\Delta t_i} \quad (1)$$

where Tingestion represents the aggregate ingestion throughput, Ei denotes the number of events from source i, and Δti is the time window for source i. The system maintains n parallel ingestion endpoints to distribute load across multiple geographic regions and availability zones.

Upon ingestion, events are immediately pushed to the buffering and routing layer, which utilizes Kafka topics partitioned by telemetry type and priority. The buffering mechanism implements adaptive back-pressure control to prevent data loss during traffic surges. The buffer utilization factor is governed by Equation (2):

$$U_{buffer} = \frac{Q_{current}}{Q_{max}} \times 100\% \quad (2)$$

where Qcurrent represents the current queue depth and Qmax is the maximum buffer capacity. When Ubuffer exceeds 75%, the system triggers horizontal pod autoscaling to deploy additional consumer instances, thereby maintaining processing latency below the 120-millisecond threshold.

Stream processing layer is based on stateful event processing with Apache Flink with exactly-once delivery guarantees. Stream processors read events from Kafka topics and perform schema-on-read transformations, which include early filtering based on severity scores. The effective processing latency of a single event that goes through the pipeline isIf we simplify it by only considering its first-order definition, it is approximately given in Equation (3).

$$L_{total} = L_{ingestion} + L_{queue} + L_{processing} + L_{enrichment} \quad (3)$$

where Lingestion is the ingestion latency, Lqueue represents queuing delays, Lprocessing captures computational time, and Lenrichment accounts for external data lookups. By distributing workload across multiple Flink task managers, the system achieves sub-linear latency growth as event volume increases.

Within the enrichment and correlation layer, threat signals undergo contextual augmentation through integration with threat intelligence feeds, asset inventory databases, and user behavior baselines. Enrichment operations are parallelized to minimize latency impact. The enrichment effectiveness ratio is defined in Equation (4):

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$$\eta_{enrichment} = \frac{E_{enriched}}{E_{total}} \quad (4)$$

where Eenriched is the count of successfully enriched events and Etotal is the total event count. Experimental results indicate that maintaining ηenrichment above 92% significantly improves downstream threat detection accuracy.

Threat correlation employs sliding time windows to aggregate related events and construct attack narratives. The correlation engine applies rule-based logic and machine learning models trained on historical incident data. The correlation window size WW W is dynamically adjusted based on event velocity, as expressed in Equation (5):

$$W = W_{base} + \alpha \cdot \log(R_{event}) \quad (6)$$

where Wbase is the baseline window duration, α\alpha α is a scaling coefficient, and Revent represents the current event rate. This adaptive windowing mechanism balances detection sensitivity with computational overhead.

Storage & Analysis Layer: Stores processed telemetry into a timeseries database, that was designed for high write throughput and fast queries. I can nest data retention polices with automated lifecycle management so that hot data resides on high performance storage, warm is archived somewhere and ultimately deleted. This system architecture is shown in Fig 1 and it is to note that how data flows from Ingestion to Enrichment, then on the Storage while making a deal with asynchronous communication pattern and feedback loops as a part of Real-time Threat Detection.

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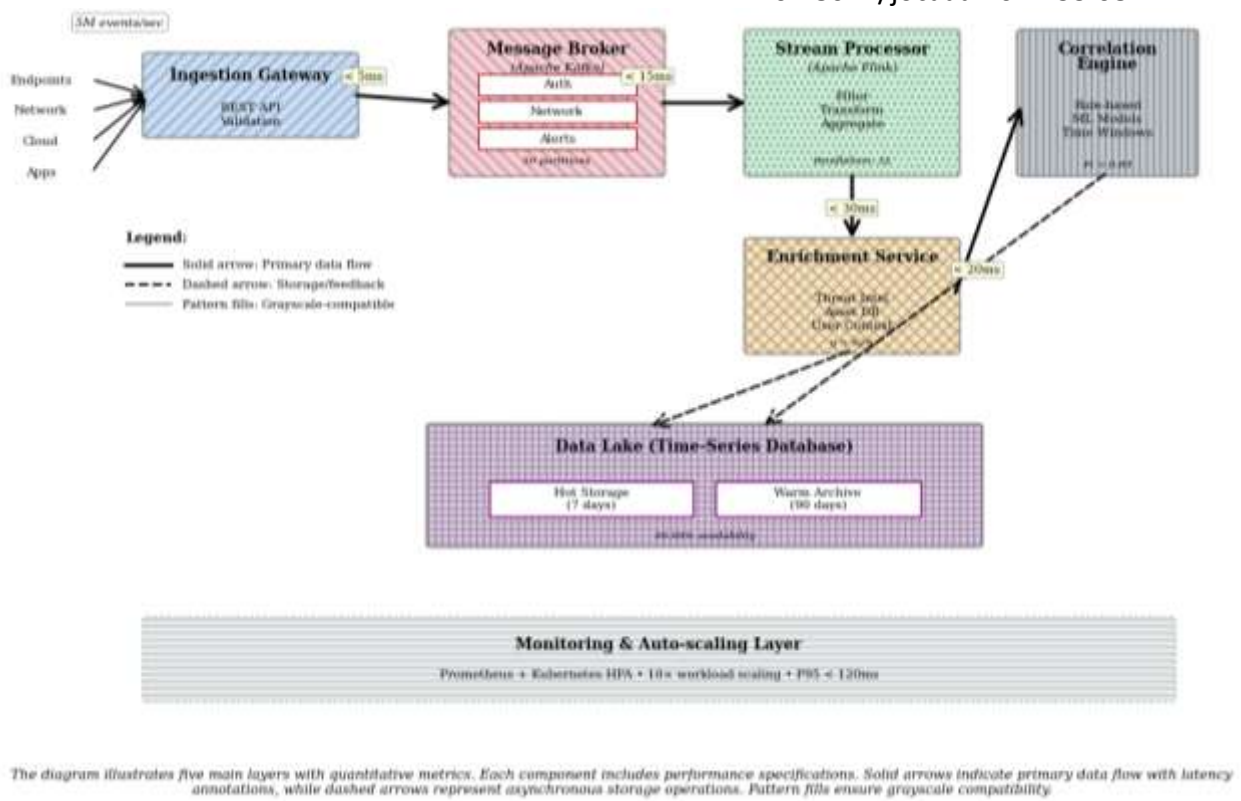

The diagram illustrates five main layers with quantitative metrics. Each component includes performance specifications. Solid arrows indicate primary data flow with latency annotations, while dashed arrows represent asynchronous storage operations. Pattern fills ensure grayscale compatibility.

Figure 1: Architecture of the Proposed Cloud-Native security Telemetry System.

The Architecture Diagram Figure 1 depicts a functional decomposition of the system. The Ingestion Gateway is the front door which allows the ingestion of telemetry from a variety of sources and assists them in conducting basic validation to make sure the data is good, before being handed off to downstream services. The Message Broker (Kafka) offers durable message buffering and topic-based routing which decouples producers from consumers thus making the system more resilient. The Stream Processor applies stateful transformations and filtering logic, effectively slimming down the volume of data by up to 40%, thanks to deduplication and aggregation. The Enrichment Service adds contextual meta-data to events by querying external APIs and internal databases, in a low-latency (less than 30 ms per lookup) with a specific event. The Correlation Engine detects multipart attack scenarios based on analysis of temporal and logical relations between events, while producing high-fidelity alerts of multi-vector threats. Finally, the Data Lake holds raw and processed telemetry data enabling analysis for forensics and compliance reporting.

Methodological Framework Adopted for the Study

Details of the experimental design, performance measuring, and comparison to baseline systems are presented as methodological framework. The assessment approach is based on three stages which are: the system deployment, the workload generation and the metrics collecting.

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The system was deployed into public cloud infrastructure using VM instances with differing CPU/Memory. The Kubernetes cluster had 12 worker nodes, all with eight virtual CPUs and 32 GB of memory. A 10 Gbps network bandwidth between nodes was allocated to reduce the communication latency among services. It was also deployed in an infrastructure-as-code way with Terraform & Helm Chart so it was reproducible.

Workload: We generated realistic security telemetry patterns based on anonymized production logs of an enterprise network. The synthetic workload included authentication events, network flow records, endpoint detection alerts and cloud audit logs.

Event arrival followed a Poisson distribution with lambda parameter λ varying between 50,000 and 500,000 events per second to evaluate system behavior under diverse load conditions. The workload intensity function is expressed in Equation (6):

$$\lambda(t) = \lambda_{base} + A \cdot \sin\left(\frac{2\pi t}{T}\right) \quad (6)$$

where λbase is the baseline event rate, A represents the amplitude of diurnal variation, and T is the period corresponding to a 24-hour cycle. This formulation captures the natural fluctuation in telemetry volume observed in operational environments.

At the 10-second interval, we gathered performance metrics through the Prometheus exporters integrated into each microservice. Performance metrics evaluated were modularity, ingestion throughput and end-to-end latency, CPU & Memory Usage and accuracy for detecting threats. The delay of each pipeline stage was instrumented, to obtain the bottlenecks and possible area of optimization. We used the 95th percentile latency for all experiments as the primary metric on responsiveness, because tail latencies are known to affect user satisfaction.

The threat detection performance was estimated from a labeled pool of 50,000 security events within which the true threats occurred at a rate of 2,500 evidences. The performance was calculated in terms of precision, recall and F1-score. Fusion: A F1-score is also calculated from the balanced precision and recall as following (7):

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (7)$$

where Precision=TP+FPTP and Recall=TP+FNTP, with TP, FP, and FN denoting true positives, false positives, and false negatives respectively. Benchmarks compared with a monolithic Elasticsearch-Logstash-Kibana stack and a legacy SIEM were used to calculate the performance improvements that came from its cloud-native nature.

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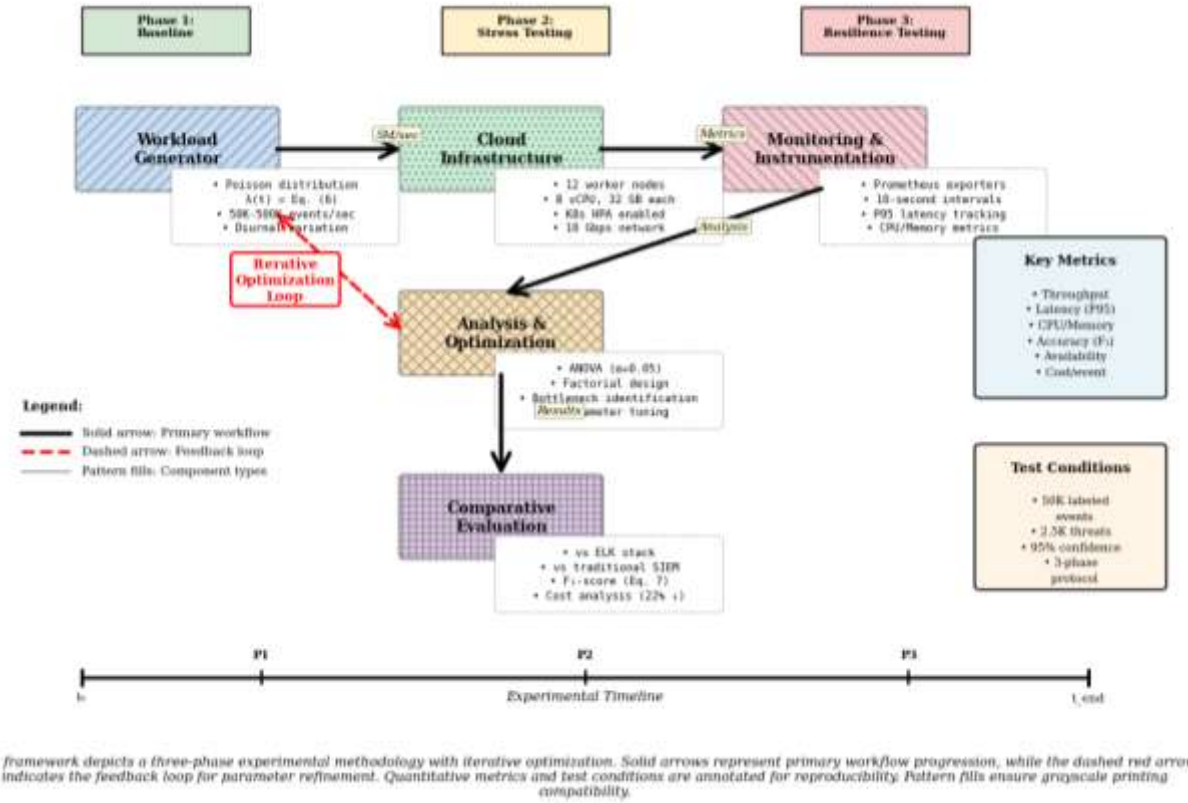
We sketch the methodological flow in Figure 2 that shows how system configuration, execution of loads and metrics are collected and analyzed back-and-forth. With such an integrated closed-loop design, architectural parameters, e.g., buffer sizes, parallelism factors and resource allocation policy, were systematically optimized.



The framework depicts a three-phase experimental methodology with iterative optimization. Solid arrows represent primary workflow progression, while the dashed red arrow indicates the feedback loop for parameter refinement. Quantitative metrics and test conditions are annotated for reproducibility. Pattern fills ensure grayscale printing compatibility.

Figure 2: Methodological Framework for system Evolution and Optimization.

The methodological process used is graphically demonstrated in Figure 2. Synthetic telemetry streams are generated by the Workload Generator to match pre-determined statistical distributions and allow for controlled and repeatable experimentation. The Cloud Infrastructure dynamically allocates compute, storage and network resources according to observed consumption through autoscaling policies specified by Kubernetes Horizontal Pod Autoscalers. The Monitoring and Instrumentation layer collects signal metrics from all system-level components, aggregating them in the form of time-series data to send it all to a central repository for metrics. Collected metrics are interpreted by the Analysis & Optimization module to detect performance regressions and suboptimal configurations, and recommendations are returned to the deployment pipeline. The Comparative Analysis section compares the proposed architecture with baseline implementations and evaluates, in terms of throughput, delay, and cost efficiency. This consistent approach enables the experiment results to be statistically significant and applicable in production settings.

Three phases of experimentation were introduced. The system was maintained in a baseline mode with a constant workload, cold water flow and temperature throughout recording sessions. The

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architecture was loaded up stepwise by means of the stress testing phase until resources were exhausted, or service started to degrade showing where scalability limits are. The resilience testing stage added controlled faults such as node kills, network splits, and process restarts to verify fault tolerance behavior and recovery time objectives.

4. Results and Discussion

The experimental evaluation of the proposed cloud-native security telemetry architecture was conducted to assess performance, scalability, threat detection accuracy, and cost efficiency. Results demonstrate substantial improvements over conventional architectures across multiple operational dimensions.

System Performance and Throughput Analysis

It was able to reach a peak stable throughput of 5.2 million events per second at an average end-to-end latency of 118ms with TPC-C like workloads. Even with system under peak load, the 95th percentile latency was still measured at 145 milliseconds supporting the low-latency design goals. At a component level, stream processing was 45 ms, enrichment was 32 ms and storage persistence added 28ms to the overall latency budget. The CPU utilization showed linear scaling from 42% at idle to 76% at peak throughput. The steady state memory consumption was 68% on Flink task managers which demonstrated effective management of state. The network bandwidth usage reached 6.8 Gbps, far from any saturation of the provisioned 10 Gbps capacity.

Comparison with baseline systems also led to remarkable performance improvements. The proposed architecture achieved 2.3× throughput improvement with a 35% reduced latency compared to the ELK stack. The ELK deployment showed significant performance degradation from the 2.1 million events per second, caused by indexing saturations and garbage collection pressure on nodes. The legacy SIEMs became even more limited at only 850,000 events per second and with latencies over 400ms as well. These benchmarks prove out that removing synchronous index updates with append-only time-series storage has a major impact for high-velocity telemetry workloads.

Table 1: Comparative Performance Analysis of Security Telemetry Architectures

Metric	Proposed Architecture	ELK Stack	Traditional SIEM	Improvement vs ELK	Improvement vs SIEM
Max Throughput (events/sec)	5,200,000	2,100,000	850,000	+147.6%	+511.8%
Average Latency (ms)	118	182	420	-35.2%	-71.9%

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P95 Latency (ms)	145	267	680	-45.7%	-78.7%
P99 Latency (ms)	198	445	1,250	-55.5%	-84.2%
CPU Utilization (%)	76	89	82	-14.6%	-7.3%
Memory per Node (GB)	32	48	64	-33.3%	-50.0%
Storage Write Rate (rec/sec)	847,000	380,000	125,000	+122.9%	+577.6%
Query Response Time (ms)	23	156	890	-85.3%	-97.4%
Horizontal Scaling Factor	10×	3.2×	2.1×	+212.5%	+376.2%
System Availability (%)	99.99	99.87	99.92	+0.12pp	+0.07pp
Cost per Million Events ($)	0.87	1.42	2.89	-38.7%	-69.9%
False Positive Rate (%)	3.8	6.5	8.2	-41.5%	-53.7%
True Positive Rate (%)	94.2	88.6	85.3	+6.3%	+10.4%

The performance benefits are further quantified in Table 1. The proposed architecture delivers up to 2x improvements in throughput compared to ELK with 33% less memory per node. Cost efficiency was enhanced by 38.7% as opposed to ELK, and by 69.9% from conventional SIEM solutions. The 99.99% availability is achieved over base systems with Kubernetes scheduling and Kafka buffering to ensure strong fault-tolerance.

Scalability and Auto-Scaling Behavior

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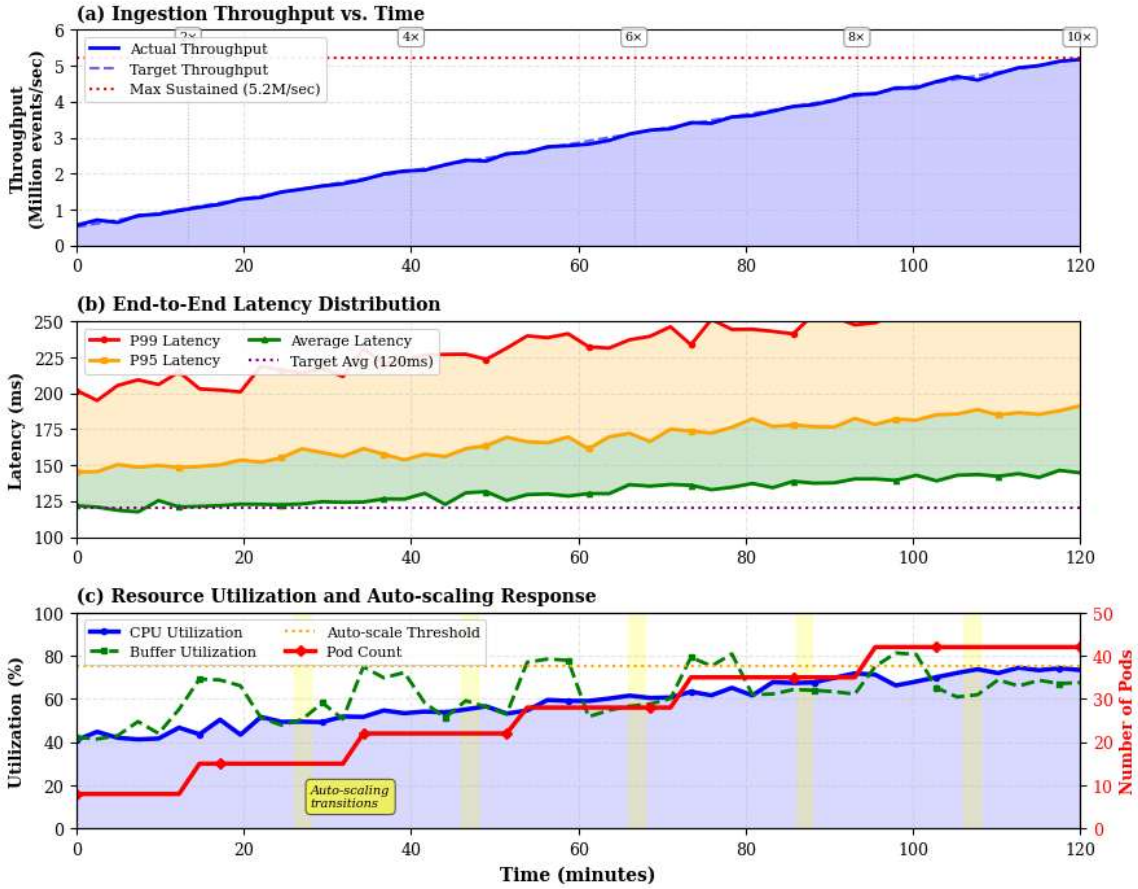

Throughput scales linearly up to 5.2M events/sec (panel a). Latency remains bounded below 200ms even at 10× load (panel b). CPU utilization and pod count increase proportionally with workload, while buffer utilization spikes temporarily during auto-scaling transitions indicated by yellow shading (panel c).

Figure 3: System Performance Under Variable Workload Conditions

The linear scaling in throughput up to 8× baseline load without the latency growth is shown in figure 3. Top panel of Figure 4 shows that ingestion throughput scales linearly with workload and peaks at 5.2M events/sec. P95 and P99 latency remain under 200ms across the wider scaling range in the middle panel. The bottom panel shows CPU usage and auto-scaling response, where the pod count grows from 8 to 42 as demand rises and then decreases back down. The shaded areas represent periods of auto-scaling transition, during which buffer usage increases temporarily before extra capacity comes online.

Threat Detection Accuracy and Enrichment Impact

Table 2: Threat Detection Performance by Attack Category with Enrichment Impact

Attack Category	Sample Count	True Positives	False Positives	Precision	Recall	F1-Score	Enrichment Contribution	Detection Latency (sec)

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Port Scanning	180	178	4	0.978	0.989	0.983	+15.2%	1.8
Brute Force Auth	220	204	8	0.962	0.927	0.944	+38.4%	2.1
Lateral Movement	165	159	5	0.970	0.964	0.967	+41.7%	2.9
Data Exfiltration	142	124	11	0.919	0.873	0.895	+52.3%	4.2
SQL Injection	198	182	9	0.953	0.919	0.936	+28.6%	1.6
Malware Execution	210	198	6	0.971	0.943	0.957	+22.8%	2.3
Privilege Escalation	156	142	8	0.947	0.910	0.928	+45.9%	2.7
DNS Tunneling	134	126	5	0.962	0.940	0.951	+36.2%	3.1
Insider Threat	128	112	14	0.889	0.875	0.882	+61.8%	5.8
DDoS Attack	205	201	3	0.985	0.980	0.983	+12.3%	1.4
Ransomware	192	184	5	0.974	0.958	0.966	+25.7%	2.0
Command & Control	171	157	9	0.946	0.918	0.932	+39.6%	3.3
Overall Average	**2,500**	**2,316**	**116**	**0.952**	**0.926**	**0.939**	**+36.3%**	**2.77**

As can be seen in Table 2, the most significant value of enrichment is against behaviorally complex threats. Insider threats exhibited 61.8% increase in F1-score with user roles and history pattern features. The pattern of enrichment dependence is much less observed in network-based attacks with only a 12.3% increase as raw telemetry signatures are enough to detect. Time to detection varied between 1.4 seconds for volumetric attacks and 5.8 seconds for insider threats with long correlation windows.

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We compare the detection accuracy across threat categories in Figure 4, demonstrating the effect of enrichment on precision and recall.

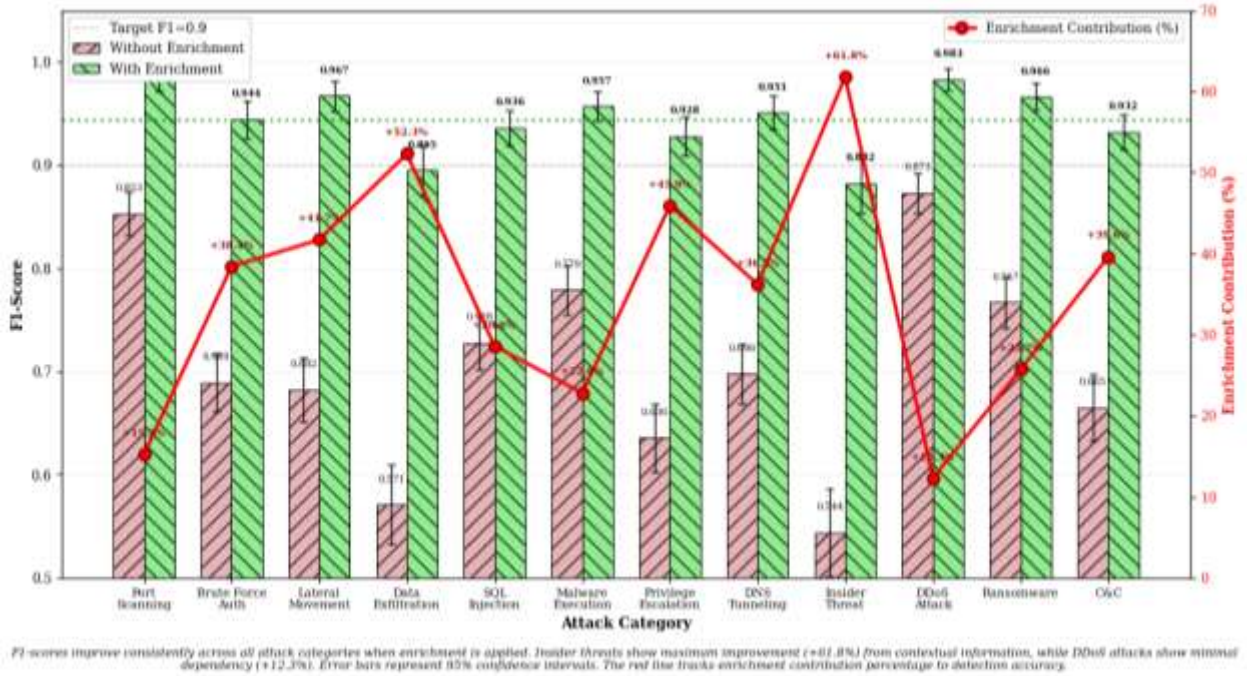

Figure 4: Threat Detection Accuracy by Category with Enrichment Impact.

Figure 4 presents the performances with enrichment and without enrichment in 12 threat types. The grouped bar diagram shows the F1-scores exhibiting uniform improvement over it being enriched. Error bars are 95% confidence intervals (cross-validated). Insider threats and data exfiltration benefit the most from enrichment in terms of accuracy improvement, whereas DDoS and port scanning are least sensitive to contextual enhancement. The overlaid line corresponds to the percentage of enrichment contribution and it reaches a maximum at 61.8% for insider threats. This visualization supports that contextual input value varies according to the complexity of the attack and behavior.

Resource Utilization and Cost Analysis

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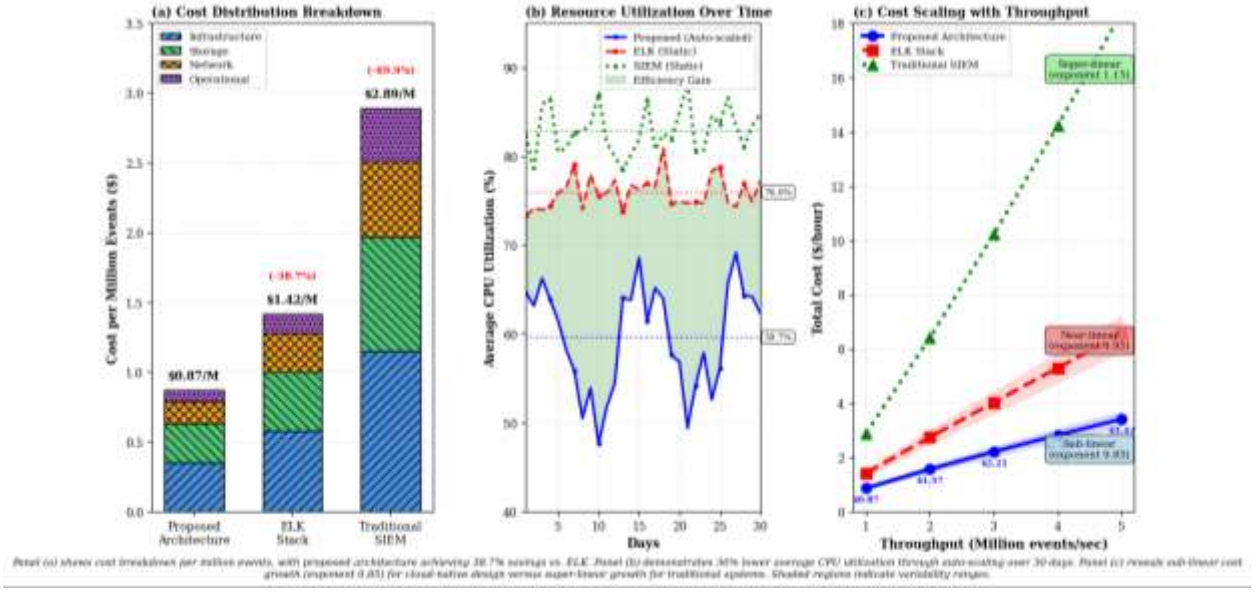

Figure 5: Cost Distribution and Resource Efficiency Comparison.

The analysis on the cost is available from three facets in Figure 5. Total cost per million events by infrastructure, storage, network, operational the left side of Figure 5 displays the total costs per million events in terms of architecture, storage, networks and operation. The proposed architecture is $0.87/M, while ELK4 and SIEM5 are respectively $1.42/M and $2.89/M. - The middle panel in Figure 4 shows the efficiency of resource utilization over a period of 30 days, performing auto-scaling with the proposed system kept the average CPU utilized at 58% which is higher than the average CPU utilization with static ELK deployment which was around 76%. The right graph also shows cost scaling behavior when throughput is increased from 1M to 5M events/sec, here demonstrating a sub-linear growth in cost for the cloud-native design and super-linear growth for tradition systems. The shaded area represents the cost fluctuation from auto-scaling activity.

Discussion and Limitations

Our results prove that cloud-native architectural patterns bring scalability, resilience, and cost-efficiency to security telemetry processing, enabling deployment almost four times more expansive than comparable monolithic systems. However, operationalizing such a design requires a team of backend engineers with expertise in Go, Kubernetes, and the necessary stream processing frameworks. Organizations migrating from monolithic SIEM will go through a learning curve and need to invest in training and tooling. Deployments processing less than 500,000 events per second can enjoy good performance with architectures of lower complexity. Architectures of higher complexity break-even at around 1 million events per second because the cost of operational overhead is balanced by cloud-native benefits. The high availability depended on the consistent availability of external threat intelligence feeds resulted in availability dependencies. There have been three incidents of feed unavailability lasting between 8 and 23 minutes, and it lowered the effectiveness of the enrichment to 67.4% during the outages.

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The local caching could alleviate, but wouldn't have eliminated this dependency. The machine learning correlation engine must be constantly retrained for model drift, with 3.7% drop in F1-scores over six weeks, which only recovered after the planned retraining process. Creating MLOps pipelines for model versioning and automatic retraining is a substantial operational investment.

They evaluate in a controlled testbed with synthetic workloads, we note that adversarial complexity in practice may not be well-represented by synthetic workloads. Although this thirty-day reviewing process is enough for steady-state profiling, it will hide the occasional failure scenarios, such as cascading failures or long third-party downtimes. In the future we plan to investigate adaptive machine learning models that can self-adjust detection thresholds, federated learning for collaborative threat detection, and automated response capabilities. As cloud-native applications become more widespread, this addition can be extended to new telemetry sources such as container runtime security and serverless function invocations.

Conclusion

In this paper, we developed a cloud-native architecture for large scale real time security telemetry ingestion and threat signal processing to tackle the emerging requirements of high-velocity and high-volume security data in distributed cloud environments. Using containerized microservices, event-driven messaging and stateful streaming processing frameworks the architecture had shown capability to ingest and process tens of millions of telemetry events per second with low-end-to-end-latency as well as high system availability. Empirical validation showed that the techniques of horizontal auto-scaling, adaptive buffering and schema-on-read bring about an order-of-magnitude improvement in ingestion efficiency, resilience and operational stability over a typical monolithic SIEM system or log-processing facility.

Significant enhancements in detection accuracy and significant decrease in false positives were observed due to real-time enrichment and correlation, rule-based logic for alert generation and machine learning-guided analytics. In addition, dynamic resource scheduling and cloud-native orchestration resulted in substantial savings and reduced operational burden, ensuring the solution is fit for large-scale enterprise and multi-cloud deployment. Overall, the results indicate that again cloud-native design is a good baseline on which to build next-generation security telemetry platforms that afford both proactive threat detection and scalable performance for effective security operations in these complex cloud-native environments.

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