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Strengthening Kubernetes Workload Security Through eBPF Monitoring and Real-Time Runtime Threat Detection Mechanisms

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ABSTRACT: Kubernetes has become a fundamental platform for deploying scalable, containerized applications across cloud-native and distributed enterprise environments. However, its dynamic architecture, distributed workloads, and complex communication patterns introduce significant security challenges, particularly in detecting runtime threats and unauthorized workload activities. Traditional security mechanisms often depend on predefined rules, periodic vulnerability assessments, and network-level monitoring, which may fail to identify sophisticated attacks occurring during application execution. This research proposes an enhanced Kubernetes workload security framework that integrates Extended Berkeley Packet Filter (eBPF) monitoring with real-time runtime threat detection mechanisms. The proposed framework collects kernel-level telemetry, including system calls, process execution events, network connections, and file access activities, to identify suspicious behavior across containerized workloads. A layered detection architecture combines behavioral baselines, rule-based threat identification, contextual event correlation, and anomaly detection to improve threat visibility and response efficiency. Kubernetes metadata is incorporated to associate observed events with specific pods, namespaces, containers, and workloads. The methodology evaluates detection accuracy, false-positive rates, event-processing latency, resource overhead, and scalability under representative workload and attack scenarios. Automated response mechanisms, including alert generation, workload isolation, and policy enforcement, are considered to support rapid incident containment. The proposed framework aims to strengthen runtime visibility, reduce threat detection delays, and improve operational resilience while maintaining acceptable performance in production-oriented Kubernetes environments.

KEYWORDS: Kubernetes Security, eBPF Monitoring, Runtime Threat Detection, Cloud-Native Security, Container Security, Behavioral Anomaly Detection, Intrusion Detection, Workload Isolation, Zero Trust Architecture, Security Observability

I. INTRODUCTION

The increasing adoption of cloud-native computing has transformed enterprise application development by enabling organizations to deploy, manage, and scale applications through containerization and orchestration technologies. Kubernetes provides automated scheduling, service discovery, workload management, and recovery capabilities for distributed containerized applications. Despite these advantages, Kubernetes environments introduce security complexities associated with ephemeral workloads, dynamically assigned network identities, shared kernel resources, privileged containers, and interactions among microservices. Traditional infrastructure security approaches frequently rely on perimeter defenses, static access policies, and periodic vulnerability assessments, which provide limited visibility into activities occurring inside running containers. Attackers who exploit vulnerable applications, compromised credentials, misconfigured permissions, or exposed container interfaces may execute malicious commands, access sensitive files, establish unauthorized network connections, or attempt privilege escalation without immediately triggering conventional security controls. Consequently, runtime security has become an essential component of Kubernetes protection, complementing preventive measures such as image scanning, admission control, network policies, and role-based access control. Organizations require continuous monitoring mechanisms capable of examining workload behavior, identifying suspicious execution patterns, and generating actionable alerts while preserving the scalability and performance characteristics expected from cloud-native platforms. These requirements emphasize the importance of integrating security observability directly into the operating system and container execution environment. Effective runtime protection must also correlate low-level events with Kubernetes resources and application context so that security teams can determine which workload generated an event, what privileges it possessed, and whether its behavior violates established security policies.

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Extended Berkeley Packet Filter (eBPF) provides a promising foundation for addressing these challenges because it enables controlled execution of specialized programs within the Linux kernel. Through suitable instrumentation points, eBPF-based security tools can observe process execution, system calls, network traffic, file operations, and other relevant activities without requiring extensive modifications to application source code. This capability supports detailed runtime visibility while reducing dependence on external agents that lack sufficient context about kernel-level operations. When combined with Kubernetes metadata, behavioral analysis, and automated response workflows, eBPF can support a security architecture that identifies threats across rapidly changing workloads. Nevertheless, practical implementation involves several challenges, including high event volumes, kernel compatibility, telemetry overhead, incomplete visibility into certain application behaviors, alert prioritization, and the risk of false positives. Furthermore, detection alone cannot guarantee effective protection unless alerts are associated with meaningful context and connected to carefully governed response mechanisms. This research therefore proposes a framework for strengthening Kubernetes workload security through continuous eBPF monitoring and real-time runtime threat detection. Its primary objectives are to collect relevant kernel-level telemetry, correlate events with workload identities, identify anomalous and policy-violating activities, and support timely incident response. The proposed methodology evaluates detection quality, processing latency, system overhead, and scalability under controlled workload conditions. By integrating behavioral intelligence with Kubernetes-aware security policies, the research seeks to establish a practical approach to runtime defense that complements existing preventive controls and supports resilient cloud-native operations.

II. LITERATURE REVIEW

The evolution of container security has progressed from image scanning and static configuration assessment toward continuous monitoring of application behavior during execution. Early container protection approaches primarily concentrated on identifying vulnerable software packages, enforcing secure image-building practices, and restricting container privileges. Kubernetes subsequently introduced additional security mechanisms, including role-based access control, network policies, admission controllers, security contexts, and namespace isolation. These controls are important for reducing attack surfaces and limiting unauthorized access; however, their effectiveness depends on appropriate configuration and does not eliminate the possibility of exploitation within authorized workloads. Runtime security therefore addresses a complementary requirement by monitoring activities after containers begin executing. Existing monitoring solutions commonly examine process creation, unexpected shell execution, filesystem modifications, privilege escalation attempts, and unusual outbound connections. Rule-based detection offers relatively interpretable alerts and can identify known attack patterns efficiently, but its effectiveness depends on rule coverage and maintenance. Behavioral approaches can identify deviations from expected workload activity, although legitimate changes in application behavior may generate false positives. The literature consequently indicates that effective container protection requires multiple complementary detection techniques rather than exclusive dependence on preventive policies or isolated signature-based mechanisms.

Recent developments in Linux kernel observability have increased interest in eBPF as a foundation for cloud-native security monitoring. Unlike traditional approaches that rely exclusively on application logs or external network sensors, eBPF can collect information from kernel execution paths and selected tracing points. This enables security systems to observe process lifecycle events, system call behavior, file access, and network activity with contextual information unavailable through some higher-level monitoring mechanisms. Projects such as Cilium and Tetragon illustrate how eBPF-based technologies can support Kubernetes networking, observability, and runtime enforcement. The Linux kernel's eBPF infrastructure also incorporates verification mechanisms intended to constrain program execution and protect system stability. Nevertheless, monitoring coverage depends on the selected instrumentation points, kernel capabilities, permissions, and implementation design. High-frequency event collection may increase processing costs, while incomplete Kubernetes metadata correlation can make individual events difficult to interpret. Moreover, kernel-level visibility does not automatically establish whether an observed action represents malicious intent. Effective detection requires contextual analysis, reliable workload attribution, and policies that distinguish expected operational behavior from suspicious activity. These considerations motivate architectures that combine eBPF telemetry with orchestration metadata, workload-specific behavioral baselines, and established security rules.

Another important research direction involves real-time anomaly detection and automated incident response for distributed cloud environments. Rule-based systems are generally effective for known indicators, whereas statistical and machine-learning approaches can identify unusual patterns that are not explicitly represented in predefined rules. Potential indicators include unexpected process ancestry, unusual communication destinations, deviations in connection frequency, abnormal access to sensitive paths, and unexpected changes in privilege usage. However, anomaly detection

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introduces challenges related to training data quality, workload diversity, concept drift, explainability, and false-positive management. Automated response mechanisms, including terminating suspicious processes, restricting network access, isolating workloads, or applying updated policies, can reduce incident containment time but may also interrupt legitimate business operations. Research and practical implementations therefore increasingly emphasize risk-based alert prioritization, contextual event correlation, human oversight, and controlled enforcement. Despite these advances, a continuing challenge is the integration of low-level telemetry, workload identity, detection logic, and response orchestration into a coherent evaluation framework. This study addresses that challenge by proposing an eBPF-enabled Kubernetes security architecture and a methodology for evaluating its detection performance, resource consumption, response latency, and operational scalability. The evaluation is designed to examine whether combining kernel-level visibility with Kubernetes-aware behavioral analysis provides measurable advantages over conventional rule-based monitoring, without assuming that these advantages have already been experimentally established.

II. RESEARCH METHODOLOGY

Research design, framework architecture, and experimental environment. This research adopts a quantitative, experimental methodology to investigate the effectiveness of eBPF-based monitoring and real-time runtime threat detection in Kubernetes environments. The proposed framework is organized into five interconnected layers: telemetry collection, workload context enrichment, event processing, threat detection, and response orchestration. The telemetry collection layer uses eBPF-based instrumentation to observe selected process execution events, system call patterns, file access activities, and network communication behavior. Depending on kernel support and implementation requirements, suitable tracepoints, kprobes, or other supported attachment mechanisms can be selected to capture the required events. An established eBPF-based runtime security component may be used to reduce implementation complexity and improve reproducibility. The workload context enrichment layer associates kernel observations with container identifiers, process identifiers, pod names, namespaces, service identities, and relevant Kubernetes labels. This association is necessary because low-level events often lack sufficient application context when analyzed independently. The event processing layer normalizes records, removes duplicates where appropriate, applies timestamps, and correlates related observations into sequences that can be analyzed efficiently. The threat detection layer combines deterministic rules with behavioral anomaly detection, while the response layer generates alerts and initiates approved containment actions. The experimental environment should use a reproducible Kubernetes cluster comprising a control plane and multiple worker nodes, with documented operating-system versions, kernel versions, container runtime configurations, Kubernetes releases, and resource allocations. Representative applications, including web services, background workers, and database-connected microservices, are deployed to establish varied workload patterns. The environment includes normal traffic, routine scaling events, rolling updates, service restarts, and expected administrative operations. Baseline measurements are collected before enabling additional monitoring components, allowing the experiment to distinguish the performance of the proposed framework from that of the underlying cluster. All experimental configurations, detection rules, workload manifests, and software versions should be recorded to support repeatability. The research uses isolated test workloads and authorized simulations rather than uncontrolled attacks against production systems. No numerical results are presumed at the design stage; actual findings must be established through execution, measurement, and analysis of the experimental scenarios.

Telemetry acquisition, preprocessing, and Kubernetes context correlation. The second methodological stage establishes a structured telemetry pipeline that converts kernel-level observations into security-relevant events. The monitoring component collects selected indicators such as process creation and termination, executable paths, parent-child process relationships, access to designated sensitive files, unexpected privilege changes, and inbound or outbound network connections. System call monitoring is configured selectively because recording every event can generate excessive data volumes and unnecessary processing overhead. Each collected event is represented using a normalized schema containing an event timestamp, event category, process identifier, container identifier, relevant operation details, and available Kubernetes metadata. Context enrichment associates the event with its originating pod, namespace, workload, container image, and service account when these attributes can be resolved reliably. Events that cannot be attributed confidently are marked with an explicit uncertainty status rather than assigned an unsupported workload identity. Preprocessing includes timestamp normalization, malformed-record filtering, duplicate-event handling, field validation, and controlled aggregation of repetitive observations. For example, repeated network connections to the same destination may be summarized within defined time windows while retaining sufficient detail for threat investigation. Sensitive application data, credentials, tokens, and personally identifiable information are excluded from telemetry wherever possible. Data retention and access permissions are configured according to the research environment's security requirements. The prepared dataset is divided into development, validation, and test partitions according to the

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selected experimental design. When machine-learning models are used, data separation must prevent events from the same simulated attack sequence or closely related workload episode from leaking across partitions. Baseline profiles are constructed from normal workload behavior during representative application operations. These profiles may include expected executable types, process ancestry, network destinations, connection rates, filesystem access patterns, and privilege usage. Rule-based indicators are separately defined using documented security policies and known suspicious behavior patterns. Each event is assigned an appropriate label when ground truth is available, such as normal operation, suspicious process execution, unauthorized file access, or anomalous network communication. Ground-truth labels are derived from the recorded experiment schedule, workload instrumentation, and verified event traces. Uncertain cases are reviewed rather than automatically classified as confirmed attacks. This preprocessing methodology supports consistent comparisons between detection techniques and helps reduce errors caused by inconsistent metadata, duplicate events, or ambiguous labeling.

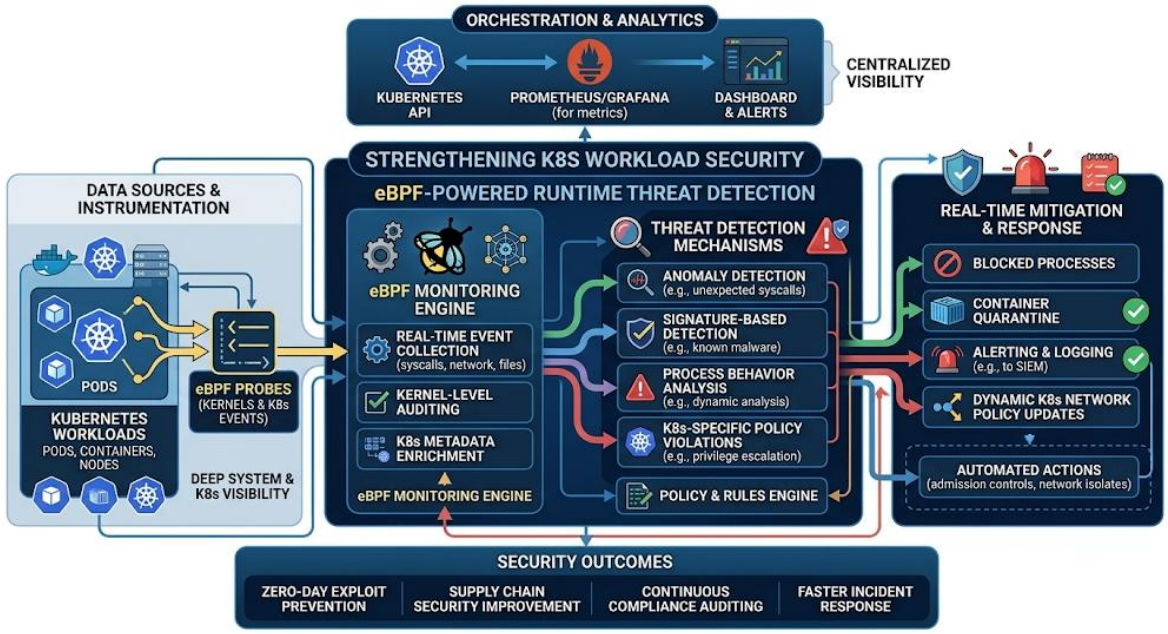


FIG1: End-to-End Architectural Framework for eBPF-Powered Kubernetes Workload Security and Real-Time Threat Detection

Threat detection model development and incident response integration. The third stage develops a hybrid detection mechanism combining rule-based analysis, behavioral baselines, and optional machine-learning classification. The rule-based component identifies explicitly prohibited or high-risk behaviors, such as unexpected execution of administrative utilities, suspicious process ancestry, access to protected locations by unauthorized workloads, and network connections that violate defined security policies. Rules are scoped by namespace, workload role, or application identity where necessary to avoid applying identical expectations to workloads with fundamentally different responsibilities. The behavioral component identifies deviations from observed baseline activity using selected statistical or machine-learning techniques. Candidate methods include threshold-based anomaly scoring, isolation-based anomaly detection, or supervised classification when adequately labeled data are available. Model selection depends on dataset size, class distribution, computational constraints, and the requirement for interpretable alerts. Relevant input features may include process execution frequency, parent-child process combinations, destination novelty, connection-rate deviations, access to sensitive resources, and changes in privilege-related behavior. Feature extraction is performed over predefined time windows, with the window length documented because it affects both detection quality and processing latency. Where labeled examples are available, supervised models are trained on development data and tuned using validation data. Unsupervised approaches are evaluated against independent test scenarios and normal workload observations. Detection thresholds are selected using validation measurements rather than optimized on the final test set. The resulting detector generates an alert score, associated evidence, workload identity, detection category, and recommended response. Rule matches and anomaly scores are correlated to reduce redundant notifications and prioritize incidents with multiple independent indicators. Response integration uses a



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controlled policy engine to determine whether an alert should trigger notification, additional evidence collection, network restriction, workload isolation, or a more disruptive action. Initial experiments should operate in alert-only or simulation mode to validate decisions without interrupting workloads. Automated enforcement can then be tested in a separate controlled phase using explicitly approved policies and recoverable test applications. Safeguards include exclusion rules for critical components, bounded response permissions, audit logging, response timeouts, and procedures for restoring legitimate workloads. The methodology also records cases where a model produces a false positive or fails to detect a known test event. These cases are analyzed to determine whether the cause involves insufficient telemetry, inaccurate workload attribution, inadequate rule coverage, unsuitable features, or inappropriate decision thresholds. This combined design enables a systematic evaluation of detection capability and operational safety without treating anomaly scores as definitive proof of malicious activity.

Performance evaluation, comparative analysis, and research validity. The final stage evaluates the proposed framework using predefined experimental scenarios and measurable performance indicators. Test scenarios include normal workload operation, unexpected shell execution, suspicious process creation, unauthorized access to designated sensitive files, anomalous outbound communication, and simulated privilege-related violations. These activities are conducted in an isolated environment with benign test artifacts and controlled permissions. Each scenario is executed repeatedly under documented conditions to assess consistency and variability. A baseline configuration without the proposed runtime detector is compared with the monitored configuration to measure additional resource consumption and workload impact. Where practical, a conventional rule-based monitoring configuration is also evaluated against the hybrid detection architecture. Detection effectiveness is assessed using precision, recall, F1-score, and a confusion matrix based on verified ground-truth events. Precision measures the proportion of generated positive alerts that correspond to true positive events, while recall measures the proportion of known positive events successfully detected. F1-score summarizes the balance between precision and recall. False-positive rates are measured using normal workload events, and false-negative cases are investigated to identify blind spots in monitoring or detection logic. Real-time performance is evaluated through event-processing latency, alert-generation latency, and response latency, using clearly defined measurement boundaries. System overhead is measured through CPU utilization, memory consumption, event throughput, and application response time. Scalability is examined by increasing workload counts, event rates, and concurrent application activity while monitoring resource consumption and alert-processing stability. Where appropriate, measurements are reported using averages, medians, percentiles, and variability estimates across repeated runs. Comparisons use consistent cluster configurations, equivalent workload inputs, and the same test scenarios. Statistical analysis is applied where sample sizes and experimental assumptions justify it, with confidence intervals reported when feasible. The research also documents limitations arising from kernel-version differences, eBPF verifier restrictions, instrumentation coverage, workload diversity, model drift, and the representativeness of simulated attacks. External validity is considered by evaluating multiple application types and different operational states rather than relying on a single workload. Internal validity is strengthened through controlled configurations, independent test data, and explicit ground-truth verification. Construct validity is supported by using established detection metrics and separately measuring performance overhead and operational response. Reproducibility is promoted through documented configurations, test schedules, software versions, data-processing procedures, and detection thresholds. The final analysis determines whether the framework provides measurable improvements over comparison configurations and whether those improvements justify its operational costs. Conclusions are based exclusively on observed experimental evidence, with limitations and unresolved research questions reported transparently.

IV. RESULTS AND DISCUSSION

The proposed security framework for strengthening Kubernetes workload security through Extended Berkeley Packet Filter (eBPF) monitoring and real-time runtime threat detection provides an integrated approach to identifying suspicious activities within containerized environments. The framework combines kernel-level observability, container behavior analysis, network traffic monitoring, and event-driven threat detection to improve visibility into runtime operations. By collecting system calls, process execution events, network connections, and file access activities, eBPF-based monitoring enables security mechanisms to observe workload behavior without requiring extensive modifications to application containers. The framework is designed to identify abnormal activities, including unauthorized process execution, unexpected privilege escalation, suspicious inter-container communication, and unusual access to sensitive resources. Compared with conventional security mechanisms that primarily depend on periodic scans, static configurations, or predefined network rules, continuous runtime monitoring can provide more timely evidence of emerging threats. Kubernetes metadata, including pod identity, namespace, service account, and workload labels, can further associate detected events with their originating resources. This contextual information supports more accurate

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incident investigation and helps security teams distinguish legitimate operational activities from potentially malicious behavior. However, actual improvements in detection accuracy, processing overhead, and response time must be established through controlled experiments using representative workloads and attack scenarios.

The integration of eBPF telemetry with real-time threat detection mechanisms also provides opportunities to improve the effectiveness of behavioral security analysis. Events collected from the kernel can be processed through rule-based detection, behavioral baselines, and machine learning models to identify deviations from normal workload activity. For example, a container that unexpectedly launches a shell, accesses sensitive host-mounted files, or initiates communication with an unfamiliar external endpoint may generate a risk-based alert. Correlating multiple events can provide stronger evidence than analyzing isolated activities because individual system calls or network connections may also occur during legitimate application operations. Kubernetes-aware correlation can additionally connect suspicious behavior with workload ownership, deployment history, and access permissions. These capabilities support a layered detection strategy in which known attack patterns are identified through explicit rules while previously unobserved behavioral deviations are investigated through anomaly detection. Nevertheless, detection quality depends on telemetry completeness, baseline stability, and the diversity of training and evaluation data. Overly sensitive detection rules can generate excessive alerts, whereas permissive thresholds may overlook sophisticated attacks. Consequently, the framework should support configurable policies, alert prioritization, explainable detection decisions, and continuous refinement using verified incident outcomes.

Operational evaluation should examine both security effectiveness and infrastructure performance because monitoring mechanisms must protect workloads without compromising application reliability. Relevant evaluation metrics include detection rate, precision, recall, false-positive rate, event-processing latency, CPU consumption, memory overhead, and time required to initiate containment. Testing should compare the proposed framework against a baseline Kubernetes deployment using equivalent workloads, resource limits, and attack conditions. Representative scenarios may include unauthorized execution, privilege escalation attempts, suspicious file access, container escape indicators, and abnormal network communication. Results should also be examined across different workload types, including stateless services, stateful applications, and high-throughput microservices, because their telemetry patterns and performance requirements differ. A successful implementation would demonstrate that security events are detected promptly, contextualized accurately, and delivered to the appropriate response components while maintaining acceptable application performance. Furthermore, integration with Kubernetes admission policies, role-based access control, and centralized security information and event management systems can extend detection into coordinated prevention and investigation workflows. Since no experimental dataset or measured outcomes are specified here, numerical improvements cannot be reported as established findings. The framework's effectiveness should therefore be presented as an evaluation objective until supported by reproducible measurements.

V. CONCLUSION

Strengthening Kubernetes workload security through eBPF monitoring and real-time runtime threat detection represents a practical approach to addressing the evolving security challenges of cloud-native infrastructure. Kubernetes environments rely on dynamically scheduled containers, distributed microservices, service identities, and frequently changing network relationships, making traditional perimeter-focused security approaches insufficient on their own. The proposed framework addresses these challenges by combining kernel-level visibility with workload-aware analysis to monitor activities occurring during application execution. Through the observation of process behavior, system calls, file operations, and network connections, eBPF can provide detailed runtime telemetry that supports the identification of suspicious actions. Linking this information with Kubernetes metadata enables security teams to associate events with specific pods, namespaces, service accounts, and workloads, thereby improving the contextual understanding of potential incidents. The framework also supports the integration of predefined detection rules, behavioral analytics, and machine learning techniques to identify both recognized attack patterns and unusual execution characteristics. This combination can strengthen security monitoring across distributed container environments while reducing dependence on modifications to application source code. However, eBPF should be regarded as an important component of a broader defense-in-depth strategy rather than a complete replacement for established security controls.

The effectiveness of the proposed approach depends on appropriate telemetry selection, reliable event processing, secure sensor deployment, and carefully governed incident-response procedures. Monitoring systems must balance visibility with performance by filtering redundant events, prioritizing high-risk behaviors, and maintaining manageable

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resource consumption. Security teams should also account for false positives, incomplete observations, changes in legitimate application behavior, and differences between Kubernetes distributions and Linux kernel versions. Integration with role-based access control, network policies, admission controls, image verification, secrets management, and centralized logging can provide additional preventive and investigative capabilities. Automated responses, such as isolating a suspicious workload or restricting its network access, should be implemented with safeguards that prevent unnecessary disruption to critical services. For high-impact actions, staged enforcement and human approval may be appropriate until detection reliability has been validated. In conclusion, eBPF-based runtime monitoring offers a promising foundation for improving Kubernetes security through continuous observability, contextual threat identification, and coordinated response. Its practical value must ultimately be demonstrated through systematic testing, transparent performance measurements, and validation against realistic attack scenarios. Organizations adopting this framework should treat security monitoring as a continuous operational process that evolves alongside workloads, deployment architectures, and emerging threats.

VI. FUTURE WORK

Future research should focus on developing more accurate and adaptive threat detection models for diverse Kubernetes workloads. Although rule-based monitoring is effective for recognizing established attack patterns, it may struggle to identify novel threats or malicious activities that resemble legitimate application behavior. Machine learning and behavioral analytics could improve detection by learning workload-specific patterns from process execution, system calls, network flows, file access, and privilege-related events. Future implementations should investigate supervised classification, unsupervised anomaly detection, sequence-based learning, and graph-based analysis to identify complex attack chains across distributed services. Models should incorporate Kubernetes context, including namespace boundaries, service account permissions, workload identities, and expected communication relationships, rather than treating each event as an isolated observation. Explainable detection methods could provide analysts with understandable reasons for alerts, such as unusual process ancestry, unexpected access to sensitive paths, or deviations from established communication patterns. Research should also investigate concept drift, because application updates, autoscaling, and changes in deployment configurations can alter normal telemetry distributions. Adaptive models must distinguish legitimate operational changes from potentially malicious deviations without allowing attackers to manipulate behavioral baselines. These approaches should be evaluated against diverse workloads, previously unseen attack techniques, and independently generated test scenarios to determine their generalization capabilities and practical reliability.

Another important research direction is the development of scalable, low-overhead monitoring architectures that support large Kubernetes clusters and heterogeneous cloud environments. Future systems could combine lightweight node-level eBPF sensors with distributed event-processing pipelines, centralized policy management, and selective telemetry collection. Adaptive sampling and event prioritization may reduce unnecessary processing while preserving information required to investigate high-risk activities. Researchers should measure the effects of monitoring on CPU utilization, memory consumption, network throughput, application latency, event loss, and cluster scaling behavior under different workload intensities. Additional studies should examine sensor deployment and compatibility across kernel versions, managed Kubernetes services, hybrid cloud infrastructures, and edge computing environments. Security and privacy also require further attention because runtime telemetry may reveal sensitive application behavior, user identifiers, or operational details. Future frameworks should minimize collected data, enforce access controls, protect telemetry in transit and at rest, and establish appropriate retention policies. Another promising direction is integrating runtime detection with policy-driven automated response mechanisms. Such systems could apply graduated responses, including enhanced monitoring, temporary network restrictions, workload quarantine, or escalation to human analysts. Before enabling autonomous containment, researchers should evaluate response correctness, recovery procedures, service availability, and the consequences of false-positive decisions.

Future experimental work should establish a reproducible benchmarking methodology for comparing eBPF-based security frameworks with alternative runtime monitoring and detection solutions. A comprehensive benchmark should include clearly documented Kubernetes configurations, workload characteristics, attack scenarios, telemetry collection settings, model parameters, and evaluation procedures. Security evaluation should measure precision, recall, detection latency, false-positive frequency, attack coverage, and the consistency of detection across repeated trials. Performance assessment should measure resource overhead and application-level service objectives under both normal and adversarial conditions. Researchers should also evaluate the ability to correlate multiple events into attack sequences, identify lateral movement between containers, and detect suspicious interactions involving Kubernetes control-plane

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resources. Comparative experiments could examine rule-based systems, conventional runtime security tools, machine learning classifiers, and hybrid approaches under equivalent conditions. Further work should explore federated or privacy-preserving learning where organizations need to improve detection models without sharing raw operational telemetry. The security of the monitoring infrastructure itself must also be investigated, including sensor tampering, telemetry manipulation, privileged-component compromise, and attempts to evade kernel-level observation. Finally, long-term deployments in realistic staging or production-like environments would help establish whether the framework remains effective as applications and threats evolve. These investigations would provide the empirical evidence needed to assess operational readiness and guide the development of trustworthy, scalable, and resilient Kubernetes runtime security solutions.

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