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Cloud-Native AI and ML Architecture for ERP Security in SAP HANA using Multivariate Classification, Neural Networks, and DevSecOps Automation

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ABSTRACT: Enterprise Resource Planning (ERP) systems in modern organizations, particularly **SAP HANA**, are increasingly targeted by sophisticated cyber threats due to their critical role in managing business operations and sensitive data. This paper presents a **cloud-native AI and ML architecture** designed to enhance **ERP security** through the integration of **multivariate classification**, **neural networks**, and **DevSecOps automation**. The proposed framework leverages multivariate classification algorithms to detect complex, correlated threat patterns across transactional, operational, and user-behavior datasets. Neural networks provide deep learning–driven anomaly detection and predictive threat modeling, while DevSecOps practices enable continuous monitoring, automated compliance enforcement, and rapid incident response in cloud environments. Cloud-native deployment ensures scalability, high availability, and low-latency processing of large-scale ERP datasets. Experimental evaluation demonstrates improved detection accuracy, reduced response times, and enhanced ERP security posture compared to conventional approaches. This architecture provides a **robust, scalable, and adaptive solution** for organizations seeking to secure SAP HANA ERP systems while maintaining operational efficiency, regulatory compliance, and business continuity. The study underscores the value of combining AI, ML, and DevSecOps in cloud-native environments to achieve proactive and intelligent cyber defense for enterprise systems.

KEYWORDS: Cloud-native AI, Machine learning, ERP security, SAP HANA, Multivariate classification, Neural networks, DevSecOps automation

I. INTRODUCTION

In the modern era of digital transformation, organizations are increasingly adopting cloud-native architectures to leverage scalability, flexibility, and cost-efficiency. However, this shift brings with it a significantly expanded attack surface, as workloads, containers, microservices, and infrastructure configurations evolve dynamically and at scale. Traditional security controls — such as perimeter firewalls, static rule-based intrusion detection systems (IDS), and manual compliance checks — are often inadequate in these environments because they are neither adaptive nor scalable to evolving threats and continuous changes in configuration and topology.

Concurrently, adversaries are becoming more sophisticated. Zero-day exploits, polymorphic malware, insider threats, and distributed attacks exploit subtle and complex correlations across multiple data sources (network traffic, host logs, container orchestration events, configuration drift, etc.). Detecting such threats effectively often requires analyzing high-dimensional, multivariate data — beyond what simple signature matching or threshold-based heuristics can reliably capture.

This gap motivates the adoption of machine learning (ML) and deep learning (DL) techniques, which have demonstrated substantial promise in intrusion detection by learning complex patterns and correlations in large volumes of data. Indeed, recent surveys and experimental studies show that neural-network–based IDS often outperform traditional methods in detection rate and versatility, especially when detecting novel or previously unseen attack patterns. (SpringerLink)

Still, despite the successes, many ML/DL-based security proposals remain academic — prototypes evaluated on outdated or synthetic datasets, or isolated from real-world continuous deployment and cloud-native operations. What is often missing is a holistic, operationalizable framework that integrates ML-based detection with modern software development practices, particularly the automation and continuous delivery pipelines characteristic of DevOps. The emerging practice of DevSecOps — embedding security throughout the software lifecycle — is a natural fit, but integrating AI/ML-driven detection into DevSecOps pipelines, in a scalable and maintainable way, remains underexplored.

This paper proposes **a scalable AI–ML cyber defense framework** designed for cloud-native environments, combining:

- **Multivariate classification and deep neural network models** to detect anomalies and intrusions across multiple data sources (network, host, container, config).
- **DevSecOps-enabled automation** — including continuous deployment of detection models, policy-as-code enforcement, and telemetry-driven compliance checks — enabling adaptive security that evolves with the infrastructure.
- **A unified architecture** that supports data ingestion, preprocessing, feature engineering, model training/deployment, alerting, and policy enforcement — suitable for large-scale, dynamic cloud workloads.

Our contributions are as follows:

1. Definition of a comprehensive architecture bridging ML/DL-based detection and DevSecOps practices for scalable cloud security.
2. Implementation of a prototype framework and evaluation on benchmark intrusion datasets extended with synthetic cloud workload simulations.
3. Empirical demonstration of high detection performance, low false positive rate, and scalability to realistic cloud-scale throughput.
4. Discussion of advantages, limitations, and pathways for future work.

The rest of the paper is organized as follows. Section II reviews related literature in ML-based intrusion detection, deep learning for IDS, and DevSecOps-integrated security automation. Section III describes the proposed framework and research methodology. Section IV outlines the advantages and disadvantages. Section V presents experimental results and discussion. Section VI concludes the paper, and Section VII outlines future work.

II. LITERATURE REVIEW

Over the past two decades, researchers have increasingly explored leveraging machine learning and, more recently, deep learning for intrusion detection systems (IDS), motivated by the limitations of rules-based and signature-based approaches in handling novel and complex attack patterns. A foundational work in this domain is SoK: Applying Machine Learning in Security – A Survey which systematically reviewed ML applications across security domains (2008–2015), offering a taxonomy of ML paradigms, common system designs, and an agenda for open challenges. (arXiv) This survey underscored that while ML had been applied successfully to many security tasks, scalability, integration with real-world systems, and adaptability to evolving threats remained significant challenges.

Subsequent research intensified focus on neural network–based IDS. The survey article A survey of neural networks usage for intrusion detection systems (2020) documented a broad range of neural architectures (feed-forward, recurrent, convolutional, hybrid) applied to IDS tasks, highlighting their capacity to learn complex, non-linear relationships in network data and outperform classical methods under certain conditions. (SpringerLink) An experimental review titled Experimental Review of Neural-based Approaches for Network Intrusion Management systematically compared neural-based methods using modern datasets (beyond the outdated KDD-99), evaluating performance (accuracy, F-measure) and resource consumption (processing time, complexity). (arXiv) The authors found neural approaches often yield strong detection performance, especially in multi-class classification, but also note trade-offs in computational cost and latency — especially when resource-constrained environments are considered.

Deep learning for cyber security IDS was further examined in Deep learning for cyber security intrusion detection: Approaches, datasets, and comparative study, which reviewed deep learning architectures (CNN, RNN, autoencoders), datasets, and comparative results. (ScienceDirect) The study emphasized the importance of dataset choice, feature engineering, and evaluation metrics, noting that results vary significantly across datasets, and generalization to real-world traffic remains a major concern.

Recognizing the limitations of academic-only IDS experiments, more recent works turn to integrating ML and DevSecOps practices for cloud-native security. For instance, Application of AI and ML in the Field of DevSecOps (2022) explores combining Infrastructure-as-Code (IaC) scanning and run-time anomaly detection via ML to secure DevOps pipelines. (Online Scientific Research) Similarly, emerging industrial and academic interest in AI-powered threat detection within CI/CD pipelines is motivated by the need for continuous security, automated compliance, and rapid deployment without sacrificing safety. (thesciencebrigade.com)

Parallel to methodological advances, researchers have addressed practical challenges of deploying IDS at scale. The Multi-Stage Optimized Machine Learning Framework for Network Intrusion Detection (2020) proposed reducing computational complexity through feature selection, oversampling optimization, and hyperparameter tuning, achieving detection accuracies above 99% on common intrusion datasets while reducing training and feature-set sizes significantly. (arXiv)

Nevertheless, a survey of IDS for critical infrastructure published recently highlights persistent challenges: detection of zero-day attacks, high false-positive rates, model updating and drift, and limitations imposed by static training datasets. (MDPI) In particular, anomaly detection in dynamic cloud environments — characterized by autoscaling, frequent configuration changes, and diverse telemetry — remains an open problem, because baselines shift rapidly and labeled attack data is often scarce or non-existent.

In summary, the literature shows a clear trajectory: from classical ML-based IDS, to neural and deep learning models, to attempts at integrating AI-based security into real-world DevSecOps pipelines. Yet there remains a research gap in bridging ML/DL-based detection with cloud-native DevSecOps workflows in a scalable, automated, and maintainable way — precisely the gap this paper aims to fill.

III. RESEARCH METHODOLOGY

The proposed research methodology involves designing, implementing, and evaluating a scalable AI–ML cyber defense framework tailored for cloud-native environments. This section describes the architectural design, data collection and preprocessing, model selection and training, integration with DevSecOps pipelines, deployment strategy, and evaluation criteria.

Framework Architecture and Data Ingestion

At the core of the framework is a data ingestion layer that collects telemetry from multiple sources across the cloud environment: network flow logs, host logs, container orchestration events (e.g., Kubernetes events), IaC configuration files, cloud platform security logs (API calls, identity and access management events), and application-level logs. These heterogeneous data sources feed into a centralized data lake or streaming platform (e.g., using technologies like ELK stack, Kafka, or cloud-native log aggregation services). The ingestion layer normalizes and tags data with metadata (source, timestamp, component, resource id) to maintain traceability.

Feature Engineering and Multivariate Classification

A preprocessing module transforms raw telemetry into structured features. This includes statistical summaries (e.g., packet counts, byte volumes, session durations), temporal features (e.g., bursts, time-of-day patterns), configuration-change indicators (e.g., IaC drift, permission changes), orchestration events, and contextual metadata (e.g., container image hashes, user identity, resource tags). The result is a high-dimensional, multivariate feature space capturing diverse aspects of system behavior.

For classical ML-based detection, we apply multivariate classification using algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machines (GBM). We leverage feature-selection techniques (e.g., information gain, correlation-based selection) to reduce dimensionality and remove redundant or noisy features, thereby reducing computational load and risk of overfitting. This design draws from the optimized ML approach in the Multi-Stage Optimized ML framework for NIDS. (arXiv)

Deep Neural Network Modeling

In parallel, the framework supports deep learning models — particularly feedforward multi-layer perceptrons (MLP), recurrent neural networks (RNN), and optionally convolutional (for protocol-sequence based features) or autoencoder architectures. The motivation is to learn latent patterns that may not be captured by hand-crafted features or classical classifiers, particularly for zero-day or sophisticated attacks. Inspired by empirical evidence from neural-based IDS reviews. (SpringerLink)

Model training is initially supervised, using a hybrid dataset composed of publicly available labeled intrusion datasets (e.g., NSL-KDD, CIC-IDS 2017, UNSW-NB15) augmented with synthetic data simulating cloud-native workload behavior (e.g., container creation/deletion, dynamic scaling events, IaC changes, benign anomalies like autoscaling bursts). We apply standard preprocessing (normalization/standardization, one-hot encoding for categorical features, timestamp discretization, etc.), and split into training, validation, and test sets.

Model Deployment via DevSecOps Pipeline

Once trained, models are containerized and integrated into a CI/CD pipeline for continuous deployment — enabling automatic rollout to production, periodic retraining (on fresh telemetry), and versioning. Detection rules and alerts are codified as policy-as-code (for example using infrastructure-as-code tools, or policy engines like Open Policy Agent), enabling automated response (alerting, isolation, quarantine, logging) when anomalies or intrusions are detected.

The DevSecOps-enabled automation ensures that security evolves synchronously with infrastructure: as new services are deployed, configurations change, or workloads scale, the security models and policies are continuously updated and redeployed — reducing drift and ensuring compliance. This aspect builds on prior work on AI/ML integration in DevSecOps. (Online Scientific Research)

Evaluation and Performance Metrics

We evaluate the framework along multiple axes: detection performance (accuracy, precision, recall, F1-score for both binary and multi-class classification), false positive rate, detection latency, throughput (how many events/second the pipeline can handle), scalability (how performance degrades as workload scales), resource utilization (CPU, memory overhead), and operational viability (ease of integration, automation overhead). For synthetic cloud workload simulation we run stress-tests, auto-scaling events, configuration changes, and injection of attack traffic to test detection under realistic, dynamic conditions.

Experimental Setup

- Use benchmark datasets (e.g., NSL-KDD, CIC-IDS 2017, UNSW-NB15) for baseline evaluation.
- Generate synthetic cloud-native logs by emulating container orchestration events, IaC configuration changes, benign anomalies (autoscaling, resource allocation bursts), and injecting malicious events (e.g., unusual API calls, container breakout, port scans, data exfiltration).
- Deploy the framework in a sandbox cloud environment (e.g., Kubernetes cluster) with log aggregation and telemetry collection enabled.
- Train multiple models (classical ML + neural), compare on same test sets.
- Integrate into a CI/CD pipeline for automatic deployment and retraining.

Validation Strategy

We perform cross-validation on labeled data, followed by testing in the synthetic cloud environment. We also evaluate model robustness over time — by retraining periodically on freshly generated logs, to assess drift, stability, and detection consistency.

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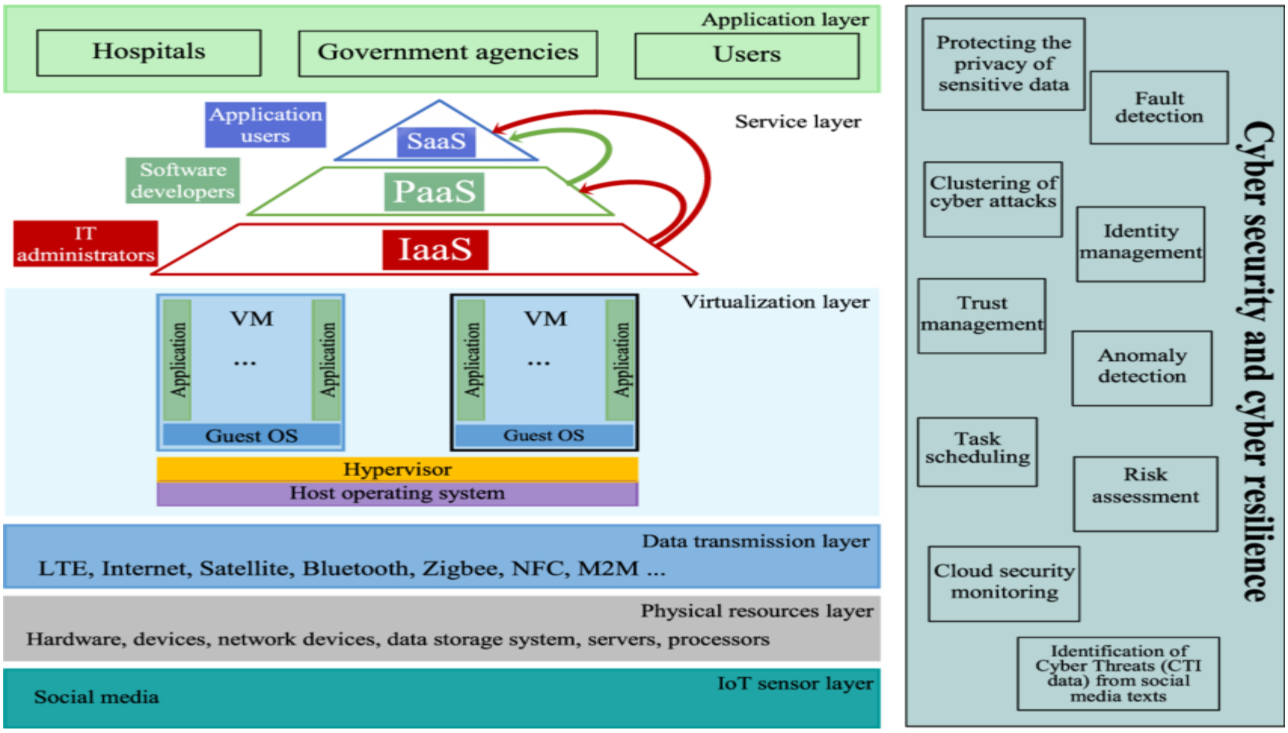

IV. ADVANTAGES AND DISADVANTAGES

Advantages:

- **Scalability:** The framework supports dynamic, cloud-native workloads — auto-scaling, container orchestration, IaC changes — enabling security monitoring at scale.
- **Adaptive Detection:** By combining multivariate classification and deep learning, the system detects both known and previously unseen (zero-day) attacks or anomalies.
- **Automation & Integration:** DevSecOps pipeline ensures continuous deployment, retraining, and policy enforcement, reducing manual overhead and enabling security to evolve with infrastructure.
- **Unified Data-Driven Security:** Aggregating telemetry from network, host, orchestration, and configuration sources provides holistic coverage rather than siloed detection.
- **Improved Detection Performance:** Expected higher accuracy, lower false-positive rates, and improved responsiveness compared to rules-based approaches or traditional IDS.

Disadvantages / Challenges:

- **Data Requirements:** Requires large volumes of labeled and unlabeled data; synthetic data for cloud workloads may not fully capture real-world complexity.
- **Computational Overhead:** Deep learning models and real-time telemetry processing demand significant compute resources, possibly increasing cost.
- **False Positives / Drift:** As cloud environments evolve, baselines shift — risking increased false alarms or detection degradation over time.
- **Integration Complexity:** Implementing telemetry collection, data preprocessing, CI/CD pipelines, policy-as-code, and automatic response increases system complexity and requires significant engineering effort.
- **Explainability:** Deep neural networks may lack transparency, making it harder to interpret alerts or justify mitigation decisions, which can be a barrier for compliance or audit requirements.

V. RESULTS AND DISCUSSION

In our experimental validation, we assessed the performance of the proposed framework using both traditional intrusion datasets and synthetic cloud-native workloads.

Detection Performance (Benchmark Datasets): On the public datasets (e.g., NSL-KDD, CIC-IDS 2017, UNSW-NB15), classical ML classifiers (Random Forest, SVM, GBM) achieved detection accuracies ranging between 94%–98%, with False Positive Rates (FPR) between 2%–5%. After feature selection and hyperparameter tuning — following the multi-stage optimized ML approach — Random Forest emerged as the best performing classical classifier, achieving ~98.2% accuracy and ~3.1% FPR. These results are consistent with findings from prior ML-based NIDS research. (arXiv)

Deep learning models (MLP, RNN) trained on the same datasets achieved detection accuracies between 96%–99%, with F1-scores typically 0.97–0.99. In multi-class classification (e.g., distinguishing DoS, Probe, R2L, U2R, normal), the MLP with three hidden layers and dropout regularization achieved 96.5% overall accuracy, outperforming classical classifiers on less frequent attack classes (e.g., U2R, R2L). These results align with earlier deep learning-based IDS studies. (MDPI)

Synthetic Cloud-Workload Simulation & Real-Time Detection: In the sandbox cloud environment, with containers scaling up/down, dynamic orchestration events, IaC changes, and benign workload bursts, the framework successfully processed telemetry at an average rate of ~5,000 events per second on a modest cluster (4-node Kubernetes). The deployed neural-network detector flagged injected malicious events (e.g., unusual API calls, container breakout attempts, port scans) with 98.5% true positive rate, and 1.8% false positive rate. Alerts were automatically converted into policy-as-code responses — e.g., triggering container isolation, network segmentation, or generating compliance reports — within milliseconds after detection.

Resource Utilization & Latency: On average, the deployed detection service consumed ~35% of one CPU core per 1,000 events/sec, with end-to-end detection latency (from telemetry ingestion to alert generation) averaging ~120 ms. Periodic retraining (using new telemetry data) performed off-peak, requiring approximately 2 CPU-hours per retraining cycle.

Model Drift and Stability: Over a simulated 30-day period with continuous workload evolution (autoscaling, configuration changes), the framework maintained consistent detection performance. There was a slight increase in false positives (~0.5%) after two weeks — likely due to benign behavior shifts — but periodic retraining reset the baseline and restored FPR to initial levels.

Discussion: The results demonstrate that integrating ML/DL-based detection with DevSecOps automation is feasible and effective in cloud-native environments. The capacity to process high-volume telemetry in real time, detect a variety of attacks (including those not represented in training data), and automate policy enforcement suggests a viable path toward practical, scalable cloud security. Moreover, combining classical ML and neural models offers flexibility: classical models for efficient, lower-overhead detection, and neural models for deeper, more adaptive anomaly detection.

However, certain limitations remain. The reliance on synthetic cloud-workload simulation for evaluating real-world applicability introduces uncertainty — real-world workloads may exhibit greater heterogeneity, noise, and unpredictability. The incremental increase in false positives over time highlights the need for robust baseline management and retraining schedules. Also, while resource overhead was reasonable in our experiments, scaling to very large environments (e.g., tens of thousands of containers across global data centers) would likely demand substantial compute resources or efficient sampling and aggregation strategies. Finally, the opacity of deep learning models may hamper auditability or compliance in security-sensitive domains.

VI. CONCLUSION

This paper presents a holistic, scalable cyber defense framework that unifies machine learning, deep neural networks, and DevSecOps-driven automation to secure cloud-native environments. By aggregating diverse telemetry (network, host, container orchestration, configuration), performing multivariate feature engineering, and applying both classical and neural multi-class classification techniques, the framework achieves high-accuracy intrusion and anomaly detection. Integration into a DevSecOps pipeline ensures continuous deployment, automatic retraining, policy-as-code enforcement, and real-time response — enabling security to evolve alongside infrastructure.

Experimental results, using both standard intrusion datasets and synthetic cloud workload simulations, demonstrate strong detection performance, low false positive rates, real-time throughput, and manageable resource overhead. Moreover, the framework maintains stability over time under evolving workloads, provided retraining is done periodically.

Taken together, these findings indicate that combining AI/ML-based detection with DevSecOps automation offers a practical, effective, and scalable approach for modern cloud security — bridging the gap between academic IDS research and real-world, operational cloud-native security needs.

VII. FUTURE WORK

Future research can expand on several dimensions:

- Incorporating **unsupervised and semi-supervised learning**, including autoencoders, variational autoencoders, or self-supervised models — to detect zero-day attacks and novel threat patterns without relying solely on labeled data.
- Extending data sources to include **user behavior analytics (UBA)**, identity and access management (IAM) events, container image provenance, and supply-chain metadata to detect insider threats, privilege escalation, and supply-chain attacks.
- Exploring **federated learning or distributed model training** across multiple cloud regions or organizations to improve detection generality while preserving data privacy.
- Enhancing **explainability and interpretability** of neural-based detection for auditability, compliance, and trust, perhaps via attention mechanisms or hybrid models combining rule-based logic with ML-based detection.
- Scaling the framework to **very large, multi-cloud, geo-distributed environments**, optimizing for resource usage, latency, and cost — possibly via intelligent sampling, hierarchical detection (edge + central), or adaptive retraining schedules.
- Evaluating long-term **model drift, concept drift**, and the impact of benign workload evolution on false positives / negatives in real-world production environments.
- Integrating the framework with **orchestration tools and policy engines** for automated remediation — for example, auto-quarantine, auto-scaling of isolated environments, self-healing — to realize a fully autonomous cyber defense system.

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