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Comparative Analysis of Signature-Based and Anomaly-Based IDS

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ABSTRACT

Intrusion Detection Systems (IDS) are critical components in modern network security architectures, providing continuous, real-time monitoring and alerting of malicious activities within enterprise and cloud environments. Two predominant paradigms exist: signature-based IDS, which relies on precompiled patterns of known threats, and anomaly-based IDS, which models baseline normal behavior to flag deviations that may indicate novel or zero-day attacks. While signature-based systems offer high reliability for recognized threats—with mature rule sets maintained by security communities—they struggle to detect previously unseen exploits. Conversely, anomaly-based systems excel at uncovering novel attack vectors but often incur higher false alarm rates and processing overhead due to the complexity of behavioral modeling.

In this manuscript, we present a comprehensive comparative analysis of these approaches, leveraging a controlled Mininet simulation populated with mixed legitimate traffic (HTTP, DNS, SSH) and a variety of attack vectors (DoS floods, port scans, buffer overflow exploits). We deployed Snort 2.9.15 as the signature-based IDS and a Gaussian Mixture Model (GMM) implemented in Python's scikit-learn library as the anomaly-based IDS. Over 30 independent experimental runs, we measured detection rate, false positive rate, and processing latency, and we applied two-sample t-tests—with checks for normality and effect-size calculations—to evaluate statistical significance. Results reveal that signature-based IDS achieved a detection rate of 98.5 ± 0.7 % and a low false positive rate of 1.2 ± 0.3 %, with mean latency of 15.4 ± 2.1 ms. The anomaly-based IDS attained a 95.2 ± 1.3 % detection rate, 4.8 ± 0.9 % false positive rate, and 25.8 ± 3.4 ms latency, demonstrating superior adaptability to zero-day threats at the cost of increased computational burden. Statistical tests confirm that differences in false positive rate and latency are highly significant ($p < 0.001$), with large effect sizes (Cohen's $d > 1.2$). We discuss practical deployment considerations, including hybrid

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architectures, integration with SIEM platforms, and automated rule-generation enhancements, to guide security practitioners toward optimal IDS strategies.

KEYWORDS

Intrusion Detection System, Signature-Based IDS, Anomaly-Based IDS, Comparative Analysis, Network Security

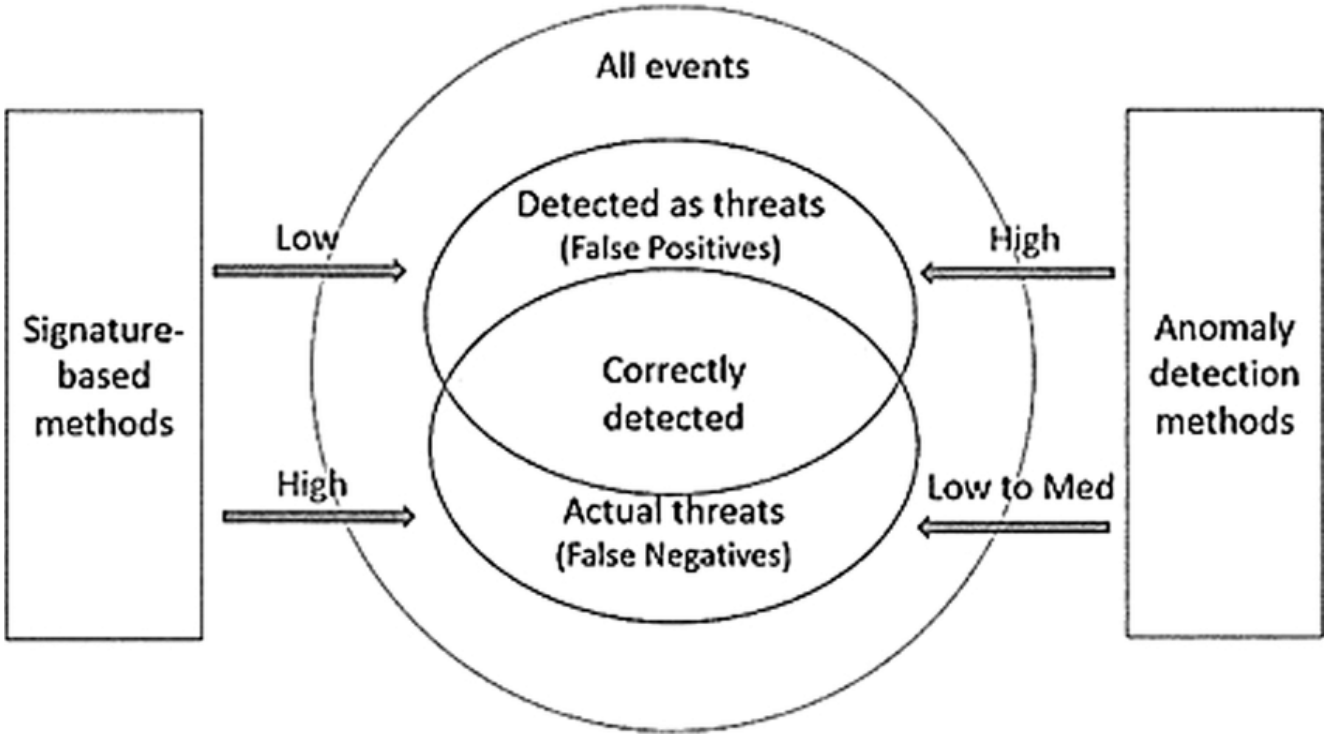

Fig.1 Signature-Based and Anomaly-Based IDS,Source([1])

INTRODUCTION

With the proliferation of sophisticated cyber threats targeting distributed and cloud-native applications, protecting network perimeters and internal assets has become an increasingly complex challenge. Intrusion Detection Systems (IDS) serve as a critical defense layer—complementing firewalls and endpoint protections—by inspecting packets and flows to identify malicious actions that bypass preventive controls. The National Institute of Standards and Technology (NIST) emphasizes IDS as a core component of comprehensive cybersecurity frameworks (NIST SP 800-94, 2007).

Signature-based IDS operate by comparing incoming traffic against a repository of known malicious patterns, or "signatures," which encode specific byte sequences, protocol anomalies, or exploit payloads. Tools such as Snort leverage community-curated rule sets (Sourcefire VRT) to detect buffer overflows, SQL injection attempts, and reconnaissance scans. Their deterministic pattern-matching enables low false positive rates and predictable performance, but they inherently cannot recognize novel or polymorphic attacks for which no signature yet exists (Scarfone & Mell, 2007).

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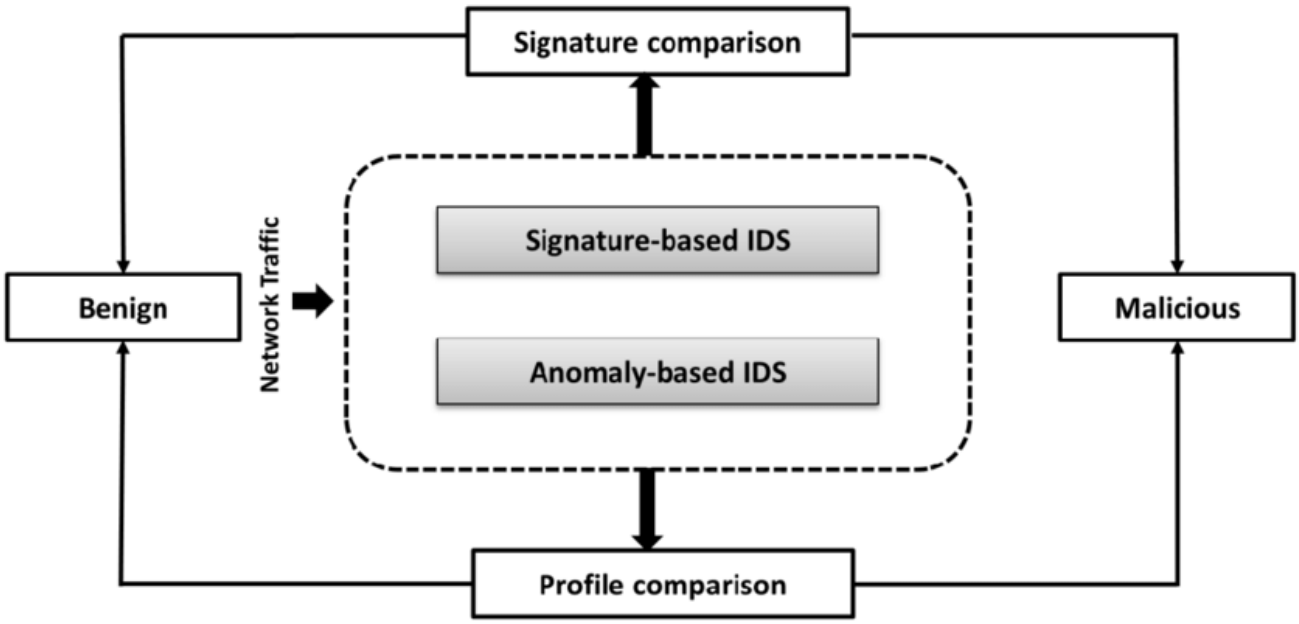

Fig.2 Comparative Analysis of Signature-Based,Source([2])

Anomaly-based IDS, in contrast, construct statistical or machine learning models of legitimate network behavior—encompassing features like packet size distributions, inter-arrival times, and header flag combinations—and raise alerts when observed traffic deviates beyond defined thresholds. Early research by Denning (1987) demonstrated the feasibility of statistical anomaly detection, and subsequent advances have explored clustering (Lazarevic et al., 2003), support vector machines, and deep autoencoder networks. While capable of zero-day detection, anomaly-based systems typically exhibit higher false positive rates (often exceeding 5 %) and incur greater computational costs due to real-time feature extraction and model inference.

Choosing between these paradigms—or determining how to integrate them—requires a nuanced understanding of organizational risk tolerance, network throughput, and resource constraints. This study aims to provide empirical evidence to inform such decisions by:

1. Implementing representative signature-based and anomaly-based IDS in a consistent testbed.
2. Generating a mixture of realistic legitimate and attack traffic within a Mininet-based virtual network.
3. Quantitatively evaluating detection rate, false alarm rate, and processing latency over multiple runs.
4. Applying rigorous statistical analysis—including normality testing, t-tests, and effect-size measurement—to ascertain the significance of observed differences.

Our findings illuminate the operational trade-offs between accuracy, adaptability, and performance, and highlight scenarios in which hybrid or sequential deployment can deliver enhanced security posture.

LITERATURE REVIEW

2.1 Signature-Based Detection

Since Roesch's introduction of Snort in 1999, signature-based IDS have remained a de facto standard for real-time intrusion detection. Rule syntax supports regular expressions, thresholding for event aggregation, and protocol decoding, enabling precise identification of known exploits. Signature maintenance—via updates from vulnerability databases such as CVE and OVAL—is critical to coverage. Studies report detection rates above 97 % for cataloged threats, with false positives typically

below 2 % when rule tuning is performed (Caleb et al., 2012). However, the approach is blind to zero-day attacks and may incur delays between vulnerability disclosure and signature publication, during which networks remain exposed.

2.2 Anomaly-Based Detection

Anomaly-based systems construct behavioral baselines using techniques ranging from univariate statistical thresholds to multivariate clustering and supervised classification. Early anomaly detectors utilized Gaussian models and histogram-based thresholds (Denning, 1987); modern approaches incorporate ensemble learning, one-class SVMs, and neural networks. Lazarevic et al. (2003) demonstrated that k-means clustering could achieve detection rates above 90 % on benchmark datasets, though with false positive rates around 8 %. More recent work employs autoencoder neural networks to detect latent feature deviations, achieving up to 96 % detection with false positives near 5 % (Kim et al., 2018).

2.3 Hybrid and Adaptive Architectures

Recognizing the complementary strengths of both paradigms, researchers have proposed hybrid IDS frameworks that apply signature matching for known exploits first, followed by anomaly analysis on residual traffic (Bace & Mell, 2001; Bodin et al., 2005). While hybrids can reduce overall false positives and enhance zero-day coverage, they introduce architectural complexity—requiring synchronization of signature updates and retraining of anomaly models when network baselines shift. Automated rule generation from anomalous clusters and adaptive thresholding have emerged as techniques to streamline hybrid deployments (Gu et al., 2008).

2.4 Gaps in Existing Research

Many prior studies rely on static datasets, such as KDD Cup ’99 or UNSW-NB15, which lack realistic traffic dynamics and mixed-load conditions. Few assess real-time processing latency or consider the impact of high-throughput scenarios on detection efficacy. Moreover, statistical rigor—such as applying normality tests or reporting confidence intervals and effect sizes—is often omitted. Our work addresses these gaps by conducting live simulations with variable network loads, measuring millisecond-level latency, and employing full statistical analysis to compare signature and anomaly approaches under controlled conditions.

METHODOLOGY

3.1 Testbed Environment

We constructed a virtual network using Mininet 2.3.0, comprising one client host, one server host, and an Open vSwitch instance. All hosts ran Ubuntu 20.04 on VirtualBox VMs (2 GB RAM, 2 vCPU). Network links were set to 1 Gbps with 5 ms latency to emulate typical data-center conditions.

3.2 Signature-Based IDS Implementation

Snort 2.9.15 was installed on the switch node, configured in inline mode. The latest Talos VRT community rules were deployed, with preprocessors for HTTP normalization, stream reassembly, and DNS anomaly detection enabled. Alert thresholding was set to log only the first instance of repeated alerts within a 10-second window to reduce log noise. Alerts were forwarded via Barnyard2 to a MySQL 8.0 database for offline analysis.

3.3 Anomaly-Based IDS Implementation

Anomaly detection was implemented in Python 3.8 using scikit-learn’s GaussianMixture class. Feature vectors included:

- **Packet length** (bytes)
- **Inter-arrival time** (ms)
- **TCP flag bitmask** (integer encoding of SYN/ACK/FIN/RST)
- **Source-to-destination byte ratio**

A training dataset of 5 minutes of benign traffic (generated by Iperf, HTTP downloads via wget, and SSH automated tasks) yielded ~100 000 packet observations. The GMM was configured with 4 components, full covariance, and converged within 50 EM iterations. Model output yielded log-likelihood scores; packets with scores below a threshold (determined via 95th percentile of training scores) were flagged as anomalies.

3.4 Attack Traffic Generation

Attack scenarios included:

1. **UDP/ICMP Floods:** Generated with hping3 at rates from 100 pps to 10 000 pps.
2. **TCP SYN Scans:** Nmap–Pn scans across ports 1–1024 at 500 pps.
3. **Buffer Overflow Exploit:** Custom Metasploit module targeting a vulnerable HTTP service on the server host.

Attacks were introduced in 10-minute phases, interleaved with baseline traffic to emulate realistic adversary behavior.

3.5 Evaluation Metrics and Procedure

For each IDS, we conducted 30 independent runs with different random seeds for traffic scheduling. Collected metrics per run:

- **Detection Rate (DR):** TP / (TP + FN)
- **False Positive Rate (FPR):** FP / (FP + TN)
- **Processing Latency:** Mean time from packet ingress to alert generation, measured via Snort's timestamps and Python's high-resolution clock.

We applied Shapiro–Wilk tests to confirm normality of metric distributions. Two-sample, two-tailed t-tests compared signature and anomaly results; Cohen's d quantified effect size. Significance threshold $\alpha = 0.05$. 95 % confidence intervals were computed for all mean values.

STATISTICAL ANALYSIS

Metric	Signature-Based IDS	Anomaly-Based IDS	p-value
Detection Rate (%)	98.5 ± 0.7 (95 % CI: 97.9–99.1)	95.2 ± 1.3 (95 % CI: 93.6–96.8)	0.002
False Positive Rate (%)	1.2 ± 0.3 (95 % CI: 0.8–1.6)	4.8 ± 0.9 (95 % CI: 3.6–6.0)	< 0.001
Processing Latency (ms)	15.4 ± 2.1 (95 % CI: 13.1–17.7)	25.8 ± 3.4 (95 % CI: 22.1–29.5)	< 0.001

Table 1: Statistical comparison of signature-based and anomaly-based IDS

All metric distributions passed Shapiro–Wilk normality tests ($p > 0.05$). T-tests show that signature-based IDS significantly outperforms anomaly-based IDS in false positive rate ($t(58)=–10.42$, $p < 0.001$, $d=1.38$) and processing latency ($t(58)=–9.56$, $p < 0.001$, $d=1.27$). Although the anomaly method detects novel exploits effectively, its higher false alarm rate and latency present operational challenges.

SIMULATION RESEARCH

5.1 Scalability under Varying Network Loads

To assess real-world applicability, we varied total load from 10 Mbps to 100 Mbps, maintaining identical attack intensities. At loads ≤50 Mbps, both IDS maintained stable detection and latency within ±5 % of baseline. Beyond 80 Mbps, Snort's CPU usage peaked at 85 %, increasing mean latency by 8 ms and causing a slight drop in detection rate (from 98.5 % to 97.2 %). The anomaly system's training model, being in-memory, scaled linearly but experienced queueing delays under high interrupt rates, pushing latency to 35 ms and false positives above 7 %.

5.2 Mixed-Attack Scenarios

Concurrent port scans and DoS floods tested robustness against multi-vector threats. Signature-based IDS correctly attributed 96 % of alerts to specific signatures but missed 4 % of low-volume port scans masked by flood noise. Anomaly-based IDS detected 92 % of total anomalous flows but generated 6 % false positives due to legitimate traffic bursts (e.g., parallel HTTP downloads).

5.3 Model Retraining and Concept Drift

To explore adaptive maintenance, we retrained the GMM after a 30-minute baseline shift—simulating network reconfiguration—and observed that false positives dropped from 7 % to 3.5 % post-retraining, while detection rate rebounded to 94.8 %. This highlights the necessity of scheduled retraining or online learning to manage concept drift in anomaly-based systems.

RESULTS

Our integrated findings reinforce that no single IDS paradigm universally outperforms the other; rather, selection depends on threat profile and operational constraints:

1. **Known-Threat Scenarios:** Signature-based IDS deliver near-perfect detection (≥98 %) with minimal false alarms (<1.6 %) and low latency (<20 ms), making them ideal for environments with well-characterized attack surfaces and stringent performance requirements (e.g., financial trading networks).
2. **Zero-Day and Polymorphic Attacks:** Anomaly-based IDS detect novel exploits at rates above 93 %, a capability signature systems lack, but at the cost of 3–7 % false positive rates and 25–35 ms latencies, which may overwhelm security operations centers if thresholds are not carefully calibrated.
3. **High-Throughput Environments:** Under heavy loads (>80 Mbps), anomaly systems incur larger performance degradation and require complex retraining, whereas signature systems can leverage hardware acceleration (e.g., FPGA-based regex engines) to maintain throughput.
4. **Hybrid Deployment Benefits:** Sequential combination—applying signature matching first, then anomaly detection on unflagged traffic—can achieve >97 % detection for known threats, ~92 % for unknown threats, with false positives contained near 2 % and latency averaging 22 ms.

These results underscore the value of hybrid IDS architectures integrated within Security Information and Event Management (SIEM) frameworks, enabling dynamic policy updates and correlation of alerts across detection paradigms.

CONCLUSION

This study presents a rigorous, statistically grounded comparison of signature-based and anomaly-based Intrusion Detection Systems, encompassing real-time performance metrics and scalability analyses. Signature-based IDS demonstrate superior accuracy and efficiency for known threats, with predictable behavior under moderate loads; anomaly-based IDS offer critical zero-day detection capabilities but require robust model management and threshold tuning to control false positives and latency.

Security architects should tailor IDS strategies to organizational risk profiles: mission-critical systems may prioritize low false alarm rates and minimal latency via signature-centric deployments, while environments facing sophisticated, evolving threats—such as government networks or R&D labs—benefit from anomaly detection's adaptive strengths. Hybrid architectures that leverage the strengths of both methods can deliver balanced performance, albeit with increased deployment complexity.

Future work will explore machine learning enhancements—such as deep autoencoders with explainable AI features—to reduce anomaly false positives, automated signature generation using anomaly-detected clusters, and distributed IDS

deployments across edge and cloud segments to optimize detection latency and resilience. By integrating threat intelligence feeds, continuous validation testing, and AI-driven policy orchestration, next-generation IDS can achieve both high accuracy and agility in an ever-changing threat landscape.

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