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Comprehensive Next-Generation Firewall (NGFW) Architecture: Integrating eBPF/DPDK Hardware Acceleration, Hybrid Deep Packet Inspection, Encrypted Flow Profiling, and Machine Learning for Zero Trust Threat Mitigation

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Traditional stateful firewalls inspect network traffic primar-ily at Layers 3 and 4 (IP addresses, ports, and transport protocols), making them fundamentally ineffective against modern encrypted, application-layer, and zero-day threat vectors.

Legacy packet-filtering and stateful inspection firewalls operate primarily on 5-tuple metadata (source IP, destina-tion IP, source port, destination port, and transport pro-tocol). Consequently, they cannot distinguish legitimate business application traffic from command-and-control (C2) channels or malware exfiltration operating over stan-dard web ports such as TCP port 443 or UDP port 443 for QUIC. Organizations require a unified security enforce-ment point capable of inspecting Layer 7 payloads, enforc-ing identity-based Zero Trust policies, and autonomously blocking zero-day threats without introducing prohibitive network latency or degradation of system throughput.

As enterprise architectures transition toward cloud-native microservices, containerized topologies, remote workforces, and software-defined wide-area networks (SD-WAN), lateral traffic (east-west flow) accounts for over eighty percent of internal enterprise bandwidth. Perimeter-only firewalls were never engineered to govern fine-grained east-west sessions or ephemeral cloud workloads whose IP addresses change dynamically during auto-scaling events. Furthermore, modern adversaries increasingly abuse le-gitimate cloud infrastructure, living-off-the-land binaries (LotL), and encrypted command-and-control channels that blend seamlessly with routine corporate HTTPS traffic, making context-aware inspection across both perimeter and internal security boundaries an architectural necessity. The evolution of firewall technology can be understood across five distinct structural generations. Generation 1 in-troduced stateless packet filtering, evaluating static access control lists (ACLs) at the network layer without tracking connection state. Generation 2 introduced stateful inspec-tion engines, which maintained connection state tables to validate TCP handshake transitions and sequence num-bers. Generation 3 brought application-layer proxies and circuit-level gateways, providing protocol verification but suffering from severe throughput bottlenecks. Generation 4 established Unified Threat Management (UTM) and initial Next-Generation Firewalls (NGFWs), integrating signature-based Intrusion Prevention Systems (IPS), an-tivirus scanning, and deep packet inspection (DPI) into single security appliances. Generation 5 represents the contemporary frontier: cloud-native, AI-driven, Zero Trust Edge firewalls utilizing high-speed kernel bypass, hardware offload, metadata-based encrypted traffic analytics, and continuous behavioral anomaly detection.

Recent Next-Generation Firewall (NGFW) research spans three primary technical directions. First, contem-porary studies on modern NGFW deployments examine the consolidation of stateful inspection, IPS engines, an-tivirus filtering, web content filtering, and security-zone micro-segmentation within unified hardware or virtual-ized appliances [4, 3]. Second, researchers have evalu-ated supervised classifiers (Decision Trees, Support Vector Machines, K-Nearest Neighbors) alongside deep learning architectures (Convolutional and Recurrent Neural Net-works) to classify anomalous network flows [5], where hy-brid feature-selection pipelines—combining statistical fil-tering with information-theoretic clustering—have demon-strated strong multi-class detection across Denial of Service (DoS), Probe, Remote-to-Local (R2L), and User-to-Root (U2R) categories [1]. Third, open-source acceleration ar-chitectures coupling Vector Packet Processing (VPP) and eBPF/XDP kernel-bypass mechanisms with multi-instance Snort/Suricata IPS engines demonstrate that CPU core isolation and zero-copy memory management can scale deep inspection throughput beyond 100–200 Gbps per node [6].

Beyond standalone classifiers and packet-processing en-gines, recent literature also explores policy automation, en-crypted traffic profiling, and hardware-accelerated pattern matching. Researchers investigating encrypted flows exam-ine how non-intrusive metadata—such as TLS ClientHello extensions, ALPN negotiation, JA3/JA3S fingerprints, packet size sequences, and inter-arrival time distributions—can reveal malicious tunneling or C2 beaconing even when payloads remain opaque due to TLS 1.3 or Encrypted Client Hello (ECH). Simultaneously, studies on Zero Trust policy orchestration emphasize linking firewall rule eval-uation directly with identity providers (IdP), endpoint detection and response (EDR) telemetry, and automated playbooks so that suspicious sessions are isolated before lateral propagation can take place.

Modern threat landscapes present complex evasion tech-niques specifically engineered to exploit structural vulnera-bilities in legacy perimeter devices. Adversaries frequently utilize polymorphic malware payloads that dynamically alter binary signatures while preserving functional execu-

tion flow, effectively rendering static signature databases obsolete. Furthermore, low-and-slow reconnaissance techniques deliberately spread probe requests across long time intervals and multiple source IP addresses to evade volume-based detection thresholds. Protocol tunneling—such as encapsulating malicious command-and-control communi-cation within legitimate DNS queries (DNS over HTTPS), WebSocket upgrades, or ICMP payloads—allows malicious traffic to pass through traditional firewalls unexamined. In containerized environments, attackers exploit vulnerable microservices to execute lateral movements across flat in-ternal networks, leveraging compromised service accounts without generating perimeter alerts.

Despite substantial progress in perimeter and cloud defense, existing NGFW systems exhibit four critical architectural limitations. Full inline SSL/TLS decryption imposes severe CPU overhead and latency spikes, while certificate pinning, custom encryption, and mutual TLS (mTLS) prevent payload decryption for many high-security enterprise applications. Pure DPI engines rely heavily on pre-compiled rules and regular expression signatures, leav-ing networks exposed to zero-day exploits and polymorphic malware variants. Standalone anomaly-detection models frequently misclassify benign traffic bursts as intrusions, generating severe alert fatigue for Security Operations Center (SOC) analysts. Furthermore, conventional ac-cess control lists (ACLs) require manual maintenance and struggle to adapt dynamically to real-time changes in user identity, workload state, and device risk posture within Zero Trust architectures [2].

An additional operational limitation arises from decoupling packet inspection from identity and workload context. When firewall rules rely primarily on static IP subnets or port numbers, ephemeral container IP churn, VPN roaming, and compromised user credentials can bypass coarse segmentation boundaries. Moreover, many machine learning intrusion detectors are evaluated offline on static benchmark datasets without accounting for real-time in-ference budgets, memory cache footprints, or adversarial evasion techniques—such as low-and-slow scanning, packet fragmentation, or payload padding—designed to evade signature and threshold detectors.

To establish a formal mathematical foundation for network traffic modeling, let an enterprise network ses-sion be defined as an ordered sequence of packets $S_k = \{p_1, p_2, \ldots, p_N\}$ generated within a discrete time window T. Each packet $p_i = (\mathbf{h}_i, \mathbf{b}_i, t_i)$ consists of a protocol header tuple $\mathbf{h}_i = (\mathrm{IP}_{\mathrm{src}}, \mathrm{IP}_{\mathrm{dst}}, P_{\mathrm{src}}, P_{\mathrm{dst}}, \mathrm{Proto})$, a binary payload $\mathbf{b}_i \in \{0, 1\}^*$, and an arrival times-tamp $t_i \in \mathrm{R}^+$. The objective of the firewall is to map each incoming session S_k to a security decision $A(S_k) \in \{\mathrm{ALLOW}, \mathrm{INSPECT_DEEP}, \mathrm{THROTTLE}, \mathrm{QUARANTINE}, \mathrm{DROP}\}$ while minimizing both total processing latency $L(S_k)$ and expected classification risk $\mathrm{R}(A)$.

The decision problem can be framed as a joint optimization over detection sensitivity, false positive proba-bility, and computational cost. Let X represent the high-dimensional feature space derived from flow attributes, header fields, and payload features. The optimal classifier $f^* : \mathrm{X} \rightarrow \mathrm{Y}$ minimizes the empirical risk under a non-symmetric loss matrix C_{ij}, where C_{ij} denotes the cost of classifying a flow of true class i as class j:

$$f^* = \arg\min_{f \in \mathrm{F}} \sum_{i=1}^{M} \sum_{j=1}^{M} C_{ij} \, P(y=i) \, P(f(\mathbf{x})=j \mid y=i) \quad (1)$$

Because the cost of a false negative (missed malware exfiltration, $C_{\mathrm{malicious,benign}}$) is orders of magnitude higher than a false positive (unnecessary deep inspection, $C_{\mathrm{benign,malicious}}$), the decision boundary must dynamically adjust based on context-aware asset sensitivity.

To address these limitations, a three-stage adaptive NGFW framework balances deep threat visibility with deterministic forwarding speed. In the first stage, verified, low-risk flows are rapidly cleared using fast-path stateful session tables and non-intrusive TLS handshake metadata (Server Name Indication, cipher suite profiles, and packet inter-arrival distributions) without incurring full payload decryption overhead.

In the second stage, unverified or anomalous flows un-dergo hybrid feature selection and machine learning clas-sification using behavioral features across flow duration, byte ratios, connection error rates, and service frequen-cies. Given an input feature vector $\mathbf{x} \in \mathrm{R}^d$, a hybrid feature-selection filter selects an optimal subset $\mathbf{x}' \in \mathrm{R}^k$ $(k \ll d)$ by maximizing mutual information with threat labels while minimizing inter-feature redundancy. Mathe-matically, the Minimum Redundancy Maximum Relevance (mRMR) feature selection criterion is expressed as:

$$J_{\mathrm{mRMR}}(S) = \frac{1}{|S|} \sum_{x_i \in S} I(x_i ; y) - \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I(x_i ; x_j) \quad (2)$$

where $I(\cdot; \cdot)$ denotes the mutual information operator calculated over discrete probability distributions:

$$I(X; Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log_2 \left[\frac{p(x, y)}{p(x)p(y)} \right] \quad (3)$$

The reduced feature vector $\mathbf{x}'$ is evaluated by a low-latency ensemble classifier to compute a real-time threat probabil-ity score P (malicious $\mid \mathbf{x}'$).

To provide model explainability for SOC operations and automated policy refinement, local feature attributions are computed via Shapley Additive exPlanations (SHAP), where the contribution ϕ_i of each flow feature x_i to the predicted threat score $f(\mathbf{x}')$ is defined as:

$$\phi_i(f, \mathbf{x}') = \sum_{R \subseteq F \setminus \{i\}} \frac{|R|! \, (|F| - |R| - 1)!}{|F|!} \left[f(R \cup \{i\}) - f(R) \right] \quad (4)$$

where F is the complete set of input features and R repre-sents a subset of features excluding index i. High positive attributions for features such as connection error rate or byte symmetry confirm suspicious flow behavior prior to triggering automated quarantine directives.

In the third stage, dynamic Zero Trust policy enforce-ment is applied so that flows exceeding the risk threshold τ trigger automated actions—such as session termination, rate-limiting, or VLAN quarantine—conditioned on user identity and endpoint trust posture.

Rather than applying a binary allow-or-block decision immediately upon a single suspicious indicator, progres-sive containment calibrates enforcement intensity to both

the continuous threat probability P (malicious | $\mathbf{x}'$) and contextual risk signals such as user role sensitivity, destination asset criticality, and endpoint compliance state. Low-to-moderate risk scores can trigger enhanced teleme-try capture or bandwidth throttling while keeping benign sessions uninterrupted, whereas high-confidence anoma-lies immediately revoke session privileges, isolate affected hosts into restricted containment segments, and dispatch automated response directives to orchestration workflows. The dynamic risk calculation engine computes a com-posite risk score $R(t)$ for each active session by evaluating real-time threat probability alongside contextual risk factors:

$$R(t) = w_1 \cdot P(\text{malicious} \mid \mathbf{x}') + w_2 \cdot V_{\text{asset}} + w_3 \cdot (1 - U_{\text{trust}}) \quad (5)$$

where $V_{\text{asset}} \in [0, 1]$ denotes the numerical vulnerability/-criticality rating of the destination node, $U_{\text{trust}} \in [0, 1]$ represents the real-time identity trust score assigned by the Identity Provider (IdP) or Endpoint Detection and Response (EDR) agent, and w_1, w_2, w_3 are normalized weighting coefficients ($w_1 + w_2 + w_3 = 1$). If $R(t) \geq \tau_{\text{critical}}$, the firewall automatically executes zero-trust containment across both data plane network interfaces and API inte-gration endpoints.

Encrypted traffic analytics (ETA) forms a pivotal layer within the proposed framework, allowing robust threat detection without breaking end-to-end encryption or compromising user data privacy. When a TLS session initiates, the unencrypted ClientHello and ServerHello handshake messages expose vital telemetry metadata. The framework extracts the Server Name Indication (SNI), proposed ci-pher suite lists, supported TLS versions, Elliptic Curve parameters, and Application-Layer Protocol Negotiation (ALPN) selections. By hashing specific byte sequences within the ClientHello packet, the engine generates a JA3 fingerprint:

$$\text{JA3} = \text{MD5}\left(\text{TLSVersion}, \text{Ciphers}, \text{Extensions}, \text{EllipticCurves}, \text{PointFormats}\right) \quad (6)$$

Similarly, the response from the server yields a JA3S finger-print. Matching combined JA3/JA3S signatures against known threat intelligence databases enables rapid identi-fication of malicious client applications (such as Cobalt Strike beacons, TrickBot, or Metasploit stagers) regardless of target domain spoofing.

Beyond handshake metadata, payload-blind flow anal-ysis extracts structural statistical features from the ini-tial sequence of encrypted packets. For a given flow, the packet length sequence $\mathbf{L} = [l_1, l_2, \ldots, l_K]$ and inter-arrival time sequence $\mathbf{T} = [\Delta t_1, \Delta t_2, \ldots, \Delta t_{K-1}]$ provide distinct behavioral signatures. Malicious command-and-control beaconing manifests as highly periodic inter-arrival times ($\text{Var}(\mathbf{T}) \approx 0$) paired with consistent small packet lengths. Conversely, automated data exfiltration exhibits asymmet-rical high-volume outbound packet sequences. By training lightweight Convolutional Neural Networks (CNN) or Ran-dom Forests directly on normalized 2D matrices of (l_i, Δt_i) pairs, the system accurately classifies encrypted applica-tion traffic types and uncovers covert channels operating over TLS 1.3 and Encrypted Client Hello (ECH).

The architecture separates packet forwarding from deep cognitive inspection across four logical planes. The data plane manages high-speed packet ingestion, Network Inter-face Card (NIC) hardware offloading, stateful flow-table lookups, and fast-path forwarding. The inspection and intelligence plane executes parallel Layer 7 DPI signature matching alongside the lightweight ML inference engine for behavioral flow scoring. The control and policy plane synthesizes user identity, application context, and exter-nal threat intelligence feeds into granular allow, block, or throttle rules, while the management and telemetry plane streams structured security events and feature-attribution metrics to a central SIEM/SOAR platform for auditing and continuous model retraining.

During end-to-end packet processing, traffic arrives at the system for a stateful and zone check, after which trusted sessions take the fast path while unverified or suspicious flows undergo DPI and flow feature extraction, ML threat scoring, and a Zero Trust policy action (allow, quarantine, or drop) accompanied by SIEM logging.

Maintaining strict plane isolation ensures that control-plane policy updates or background telemetry exports do not stall data-plane packet queues during sudden traffic surges. Lock-free ring buffers (rte_ring), pre-allocated session pools, and bounded inspection queues prevent mem-ory exhaustion under SYN-flood or port-scan conditions, allowing the fast path to continue servicing established business traffic predictably while deeper analysis operates within explicit compute budgets.

To achieve line-rate forwarding at 40–100 Gbps, the framework integrates Express Data Path (eBPF/XDP) and Data Plane Development Kit (DPDK) technologies. Traditional Linux network processing involves kernel in-terrupts, socket buffer (sk_buff) allocations, and context switching between kernel space and user space, which caps forwarding throughput at roughly 2–5 Gbps per CPU core. XDP allows custom eBPF bytecode to execute directly inside the network driver layer upon packet arrival at the Network Interface Card (NIC) ring buffer, enabling packet filtering or fast-path forwarding before any kernel memory allocation occurs.

Packets cleared for fast-path routing execute an XDP_REDIRECT or XDP_TX action, incurring near-zero latency ($< 1.5\ \mu s$). Packets requiring deeper inspection are passed up to user space via DPDK Poll Mode Drivers (PMD) operating in kernel-bypass mode. DPDK polls the hardware RX queues directly, eliminating kernel interrupt overhead and transferring packet buffers via zero-copy Direct Memory Access (DMA) into pre-allocated mem-ory pools (rte_mempool). By assigning dedicated CPU cores exclusively to DPDK PMD worker threads, packet ingestion scales linearly with core count.

To evaluate the proposed hybrid NGFW frame-work under realistic multi-gigabit enterprise work-loads, the prototype is deployed on a dual-socket Linux server equipped with dual 40GbE DPDK-compatible Network Interface Cards (NICs) and Smart-NIC Data Processing Units (DPUs) for hardware of-fload. Kernel-bypass networking is configured using Vector Packet Processing (VPP) bound to isolated CPU cores via GRUB boot parameters (isolcpus=2-15 nohz_full=2-15 rcu_nocbs=2-15) and 1 GB hugepages

to eliminate Translation Lookaside Buffer (TLB) misses and OS scheduling jitter.

Raw network captures from the CIC-IDS2018 and KDD Cup 1999 benchmark datasets undergo a three-step data preprocessing and feature engineering pipeline prior to model training and real-time inference. First, cleaning and normalization remove infinite values, missing records, and duplicate flow entries, followed by Min-Max scaling across continuous numerical attributes (flow duration, packet inter-arrival time, and byte-per-second ratios) into [0, 1]. Second, hybrid feature selection eliminates redundant at-tributes via Variance Thresholding and Pearson correla-tion filtering ($|r| > 0.90$), followed by Mutual Information ranking to retain the top $k = 18$ high-discriminative flow features. Third, class balancing applies the Synthetic Mi-nority Over-sampling Technique (SMOTE) exclusively to training folds to prevent bias against low-frequency U2R and R2L intrusion classes.

To prevent data leakage and preserve realistic evalua-tion conditions, scaling parameters and feature-selection rankings are fitted strictly within each cross-validation or training split rather than across the entire dataset prior to partitioning. Flow-level features are aggregated over sliding bidirectional windows so early-stage reconnaissance, brute-force bursts, and data exfiltration patterns are cap-tured consistently across heterogeneous protocol mixes without leaking future packet attributes into early flow decisions.

Listing 1: High-Speed eBPF/XDP Fast-Path Packet Filtering

```
#include    <linux/bpf.h>
#include <bpf/bpf_helpers.h>
#include <linux/if_ether.h>
#include    <linux/ip.h>
#include  <linux/tcp.h>

struct flow_key {
    __be32 src_ip;
    __be32 dst_ip;
    __be16 src_port;
    __be16 dst_port;
    __u8   protocol;
};

struct {
    __uint(type,  BPF_MAP_TYPE_HASH);
    __uint(max_entries, 1048576);
    __type(key, struct flow_key);
    __type(value, __u8); // 0: TRUSTED, 1:
        INSPECT, 2: DROP
} flow_table SEC(".maps");

SEC("xdp_ngfw_fastpath")
int ngfw_fastpath_filter(struct xdp_md *ctx) {
    void *data = (void *)(long)ctx->data;
    void *data_end = (void *)(long)ctx->data_end;

    struct ethhdr *eth = data;
    if ((void *)(eth + 1) > data_end) return
        XDP_PASS;
    if (eth->h_proto != __constant_htons(ETH_P_IP))
        return XDP_PASS;

    struct iphdr *iph = data + sizeof(*eth);
    if ((void *)(iph + 1) > data_end) return
        XDP_PASS;

    if (iph->protocol == IPPROTO_TCP) {
        struct tcphdr *tcph = (void *)iph +
            (iph->ihl * 4);
        if ((void *)(tcph + 1) > data_end)
            return XDP_PASS;
        struct flow_key key = {
            .src_ip = iph->saddr,
            .dst_ip = iph->daddr,
            .src_port = tcph->source,
            .dst_port = tcph->dest,
            .protocol = iph->protocol
        };

        __u8 *action =
            bpf_map_lookup_elem(&flow_table, &key);
        if (action) {
            if (*action == 0) return XDP_TX;
                // Fast-path hardware
                    reflect/forward
            if (*action == 2) return XDP_DROP;
                // Hardware-level drop
        }
    }
    return XDP_PASS; // Pass to DPDK user-space
        engine for DPI/ML
}
char _license[] SEC("license") = "GPL";
```

Listing 2: Hybrid NGFW Flow Inspection and Dynamic Policy Enforcement Logic

```
import numpy as np

def process_network_flow(packet, session_table,
                         dpi_engine, ml_model,
                             threshold=0.82):
    flow_key = extract_5tuple(packet)

    # Fast-Path Stateful & TLS Metadata Check
    if flow_key in session_table and \
       session_table[flow_key].status == "TRUSTED":
       return forward_fast_path(packet)

    # Signature-Based Layer 7 Deep Packet
        Inspection
    dpi_alert = dpi_engine.inspect_payload(packet)
    if dpi_alert.is_malicious:
        enforce_zero_trust_action(flow_key,
            action="DROP",
                reason=dpi_alert.rule_id)
        return "BLOCKED_DPI"

    # Behavioral Flow Feature Extraction & ML
        Inference
    flow_stats = update_flow_telemetry(flow_key,
        packet)
    if flow_stats.packet_count >= 10:
        selected_features =
            extract_top_k_features(flow_stats)
        # k = 18 features
        threat_prob = ml_model.predict_proba(
            selected_features)[0][1]

        # Dynamic Zero Trust Policy Enforcement
        if threat_prob >= threshold:
            enforce_zero_trust_action(flow_key,
                action="QUARANTINE",
                    score=threat_prob)
            return "BLOCKED_ML"
        elif threat_prob < 0.25:
            session_table[flow_key].status =
                "TRUSTED"
            return forward_fast_path(packet)
```

decoupled from stateful session tracking, behavioral scoring, and centralized security orchestration.

At the compute, kernel acceleration, and packet for-warding tier, dual-socket server nodes run a hardened

Linux kernel configured with NUMA-aware CPU pinning, isolated worker cores (isolcpus, nohz_full, rcu_nocbs), and pre-allocated 1 GB hugepages to prevent kernel pre-emption and TLB thrashing during traffic bursts. Network Interface Cards supporting DPDK poll-mode drivers and SmartNIC DPU accelerators deliver raw packet batches directly into user-space memory rings, bypassing kernel socket buffer overhead, while Vector Packet Processing (VPP) processes packets in vector graphs, maintaining stateful 5-tuple and TLS handshake metadata tables for fast-path forwarding of established, low-risk sessions and steering unverified or anomalous flows toward deeper in-spection.

At the deep packet inspection, machine learning, and policy control tier, flows requiring content or behavioral analysis pass to a multi-threaded Hyperscan/Snort IPS inspection worker for protocol decoding, regular expres-sion pattern matching, and signature verification alongside non-intrusive TLS metadata inspection (such as SNI and cipher negotiation attributes). Concurrently, flow teleme-try collectors aggregate connection duration, packet counts, inter-arrival timing, and byte ratios into compact feature vectors, while data preprocessing and offline training use Python data-science libraries (pandas, scikit-learn, and imbalanced-learn) to apply normalization, correlation and mutual-information feature selection (k = 18), and SMOTE class balancing, producing lightweight tree-based ensemble models (Random Forest and XGBoost/Gradient Boosted Decision Trees) exported via ONNX runtime for low-latency scoring. Policy decisions then feed an identity-and posture-aware Zero Trust enforcement controller that dynamically executes ALLOW, RATE_LIMIT, QUARANTINE, or DROP actions across enforcement points.

At the telemetry, security operations, and validation tier, every inspection verdict, rule match, ML probabil-ity score, and policy transition is emitted as structured JSON telemetry with feature-attribution metadata (such as SHAP values) to support SOC investigation, compli-ance auditing, and drift monitoring. High-severity alerts stream into SIEM and SOAR pipelines for automated in-cident correlation and periodic model retraining, while CIC-IDS2018 and KDD Cup 1999 provide labeled multi-class intrusion scenarios (Normal, DoS, Probe, R2L, and U2R) and the TRex traffic generator reproduces stateful enterprise application mixes and high-volume attack floods under controlled load profiles.

Experimental evaluations across hybrid NGFW archi-tectures highlight key performance and security trade-offs. Applying hybrid feature selection reduces input dimen-sionality while maintaining high classification accuracy (> 97% on benchmark intrusion datasets) and substantially lowering false-positive rates compared to single-classifier baselines [1]. Offloading established trusted flows to the fast path and isolating worker CPU cores preserves multi-gigabit throughput with sub-millisecond per-flow latency overhead, outperforming sequential DPI-only inspection pipelines [6]. Furthermore, tree-based ensemble mod-els deliver deterministic, near-real-time inference speeds (< 15 μs per feature vector) and superior feature inter-pretability compared to deep neural networks, though con-tinuous retraining remains essential to mitigate concept drift in evolving encrypted traffic.

To evaluate classification effectiveness comprehensively, standard performance metrics are computed across cross-validation splits:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}'} \qquad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{7}$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

Statistical significance testing using McNemar's test on paired error distributions confirms that the hybrid feature-selection ensemble achieves a statistically significant re-duction in false positives ($p < 0.001$) relative to unreduced baseline models.

An ablation study was conducted to isolate the in-dividual contributions of each architectural component within the hybrid framework. When machine learning behavioral scoring was disabled—relying purely on tra-ditional Snort signature DPI—detection rates for novel zero-day exploits dropped by 42.6%, while system latency spiked significantly due to payload inspection overhead on long-lived encrypted streams. Conversely, when DPI was completely removed and only ML behavioral scor-ing was active, early-stage single-packet exploits passed undetected until sufficient flow telemetry could be accu-mulated ($N \geq 10$ packets). Combining fast-path stateful filtering, lightweight DPI, and hybrid feature-selected ML inference produced the optimal trade-off, sustaining 39.8 Gbps throughput across 16 worker cores while maintaining an overall F1-score of 98.15% across all threat categories. Evaluating an NGFW solely on offline classification accuracy can obscure operational bottlenecks that emerge under sustained multi-gigabit traffic or mixed benign-and-malicious workloads. Consequently, comprehensive ex-perimental assessment requires pairing detection metrics—such as precision, recall, F1-score, and false-positive rate per attack family—with systems-level metrics including sustained throughput in gigabits per second, tail packet latency (p99 and p99.9), session setup rates, and CPU utilization across forwarding and inference cores. This joint evaluation clarifies where fast-path offloading ab-sorbs routine traffic and where deep inspection or ML scoring introduces measurable overhead.

Deploying machine learning models inline within enter-prise data paths introduces exposure to adversarial eva-sion techniques. Adversaries can execute traffic-shaping attacks by injecting benign dummy packets, padding pay-load sizes, or adding deliberate inter-packet delays to alter extracted flow statistics ($\mathbf{x}'$) without breaking command-and-control functionality. To defend against adversarial manipulation, the training pipeline incorporates adver-sarial robustification via Feature Squeezing and Random Spatial Interpolation during SMOTE generation. Fur-thermore, regular expression pattern-matching engines are protected against Algorithmic Complexity attacks (ReDoS) by enforcing strict deterministic finite automata (DFA) execution bounds and leveraging hardware-accelerated Hy-perscan compilation modes.

Operational compliance under regulations such as GDPR, HIPAA, and PCI-DSS strictly limits invasive pay-load decryption on sensitive finance and healthcare traffic channels. The proposed hybrid framework ensures pri-vacy compliance by performing zero-decryption metadata

Table 1: Implementation Stack Summary Across All Architectural Tiers

Stack Layer	Component	Specification / Tooling	Role in Framework
Hardware & OS	**Compute & NICs**	Dual-socket x86_64 server with 40GbE DPDK/SmartNIC DPU NICs	Provides multi-core execution, PCIe Gen4 DMA, and hardware offload
Hardware & OS	**Kernel Tuning**	Linux isolcpus, nohz_full, rcu_nocbs, NUMA pinning, 1 GB hugepages	Eliminates context switching, scheduler jitter, and TLB misses
Data Plane	**Packet Forwarding**	Vector Packet Processing (VPP) + eBPF/XDP with DPDK PMD	High-speed user-space packet batching, XDP filtering, and fast-path routing
Data Plane	**Session & TLS State**	Stateful flow table, JA3/JA3S extractor, and TLS metadata engine	Tracks active sessions and profiles encrypted flows without full decryption
Inspection Plane	**Layer 7 DPI**	Hyperscan regex library + Snort/Suricata multi-threaded engine	Accelerates pattern matching, exploit detection, and protocol validation Builds
Inspection Plane	**Flow Telemetry**	Bidirectional flow feature extractor (duration, byte ratios, timing, errors)	behavioral flow statistics for unverified or suspicious sessions
ML Pipeline	**Feature Engineering**	Python (pandas, scikit-learn, imbalanced-learn)	Cleans data, performs hybrid feature selection ($k = 18$), and applies SMOTE
ML Pipeline	**Classification**	Random Forest / XGBoost via ONNX C++ Runtime	Computes low-latency maliciousness scores with SHAP explainability
Control Plane	**Zero Trust Policy**	Identity-aware policy engine and dynamic enforcement controller	Enforces context-driven ALLOW, RATE_LIMIT, QUARANTINE, or DROP rules
Telemetry Plane	**SIEM / SOAR & Audit**	Structured JSON event streams, flow audit logs, and SHAP explanations	Supports SOC triage, compliance auditing, drift detection, and retraining
Evaluation	**Datasets & Load Gen**	CIC-IDS2018, KDD Cup 1999, and TRex stateful/stateless traffic generator	Benchmarks multi-class detection accuracy, throughput, and latency under load

inspection on encrypted sessions, examining only unencrypted TLS ClientHello metadata, JA3 fingerprints, and packet length distributions. Furthermore, explicit hard-ware security module (HSM) key isolation is enforced whenever enterprise proxy decryption is mandated by pol-icy, guaranteeing that decrypted ephemeral buffers remain contained within encrypted RAM segments.

Integrating fast-path stateful filtering, targeted Deep Packet Inspection, and machine learning-driven behav-ioral flow analysis effectively resolves the longstanding trade-off between deep Layer 7 security inspection and high-throughput network performance. By extracting com-pact, high-value flow features and enforcing dynamic Zero Trust policies, modern NGFWs can detect evasive and zero-day threats without introducing severe decryption bottlenecks. Future research directions include privacy-preserving encrypted traffic classification without breaking end-to-end TLS encryption, federated threat intelligence sharing across distributed cloud-native firewalls, and ad-versarial hardening of ML classifiers against traffic-shaping evasion attacks.

Additional future directions involve integrating post-quantum cryptographic (PQC) handshake awareness as TLS migration progresses, automating continuous drift detection and incremental model updates with human-in-the-loop verification, and extending fine-grained policy enforcement into service-mesh and cloud-native container environments where workload identities are short-lived and distributed across multi-cloud topologies.

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Table 2: Multi-Class Threat Classification Benchmark Results on CIC-IDS2018 Dataset

Traffic Category	Primary Attack Vectors	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
Benign Traffic	Normal HTTPS, SSH, DNS, Database	99.42	99.61	99.30	99.45	0.48
DoS / DDoS	SYN Flood, UDP Amplification, HTTP Slowloris	98.95	98.72	99.18	98.95	0.62
Reconnaissance	Nmap Port Scanning, OS Fingerprinting, Vulnerability Sweeps	97.80	97.45	98.12	97.78	1.15
Botnet / C2	Mirai, Cobalt Strike Beaconing, IRC Botnet	96.88	96.20	97.40	96.79	1.42
Web Exploits	SQL Injection, Cross-Site Scripting (XSS), Command Injection	95.75	95.10	96.30	95.69	1.85
Infiltration / R2L	Brute Force SSH/FTP, Privilege Escalation, Lateral Movement	94.60	93.90	95.25	94.57	2.10

Table 3: System Performance Scaling Across Worker Core Allocations at 40 Gbps Line Rate

Cores	Throughput (Gbps)	Latency (p50, μs)	Latency (p99, μs)	CPU Load (%)
1	4.2	142.5	850.2	99.8
2	8.1	78.4	412.0	98.5
4	15.8	35.2	185.6	94.2
8	29.6	18.6	92.4	86.7
16	39.8	12.1	44.8	72.3