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ADAPTIVE HYBRID ENSEMBLE FRAMEWORK FOR REAL-TIME ANOMALY DETECTION IN LARGE-SCALE DATA STREAMS

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Annotation. This paper presents an adaptive ensemble framework for real-time anomaly detection in large-scale data streams, addressing the challenges of concept drift, high-velocity data processing, and computational efficiency in modern distributed systems. We propose a Hybrid Statistical-Machine Learning Anomaly Detection (HSML-AD) algorithm that combines sliding window-based statistical analysis with incremental machine learning techniques. The framework employs a three-tier architecture: (1) lightweight statistical pre-filtering using modified Z-score and interquartile range methods, (2) adaptive feature extraction through exponential moving averages, and (3) ensemble classification using online random forest with dynamic weight adjustment based on recent prediction accuracy. Experimental evaluation on five benchmark datasets (KDD Cup 99, NSL-KDD, CICIDS2017, Yahoo S5, and Numenta Anomaly Benchmark) demonstrates that HSML-AD achieves an average F1-score of 94.3%, precision of 93.8%, and recall of 94.7%, outperforming baseline methods including Isolation Forest (F1: 87.2%), LSTM-Autoencoder (F1: 89.6%), and SPOT (F1: 86.4%). The algorithm maintains processing throughput of 127,000 records per second with average latency of 7.8 milliseconds on commodity hardware. The novelty lies in the adaptive weight mechanism that dynamically adjusts ensemble components based on data stream characteristics and recent performance, coupled with a memory-efficient incremental learning strategy that limits model size to 45 MB while maintaining detection accuracy.
The proposed framework is applicable to network intrusion detection, IoT sensor monitoring, financial fraud detection, and industrial system health monitoring, particularly in resource-constrained environments requiring real-time processing.

Keywords: anomaly detection, data streams, ensemble learning, concept drift, real-time processing, adaptive algorithms, machine learning.

KATTA HAJMLI MA'LUMOTLAR OQIMIDA REAL VAQT REJIMIDA ANOMALIYALARNI ANIQLASH UCHUN MOSLASHUVCHAN GIBRID ANSAMBL FREYMVORK

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Annotatsiya. Ushbu maqolada katta hajmli ma’lumotlar oqimida real vaqt rejimida anomaliyalarni aniqlash uchun moslashuvchan ansambl freymvork taqdim etiladi. Unda kontseptual siljish (concept drift), yuqori tezlikda keluvchi ma’lumotlarni qayta ishlash va zamonaviy taqsimlangan tizimlarda hisoblash samaradorligini ta’minlash bilan bogʻliq muammolar koʻrib chiqiladi. Mualliflar siljiydigan oyna asosidagi statistik tahlil va inkremental mashinali oʻqitish usullarini birlashtiruvchi Gibrid Statistik–Mashinali Oʻqitishga Asoslangan Anomaliyalarni Aniqlash (HSML-AD) algoritmini taklif etadilar. Freymvork uch pogʻonali arxitekturaga ega: (1) modifikatsiyalangan Z-baho va interkvartil oraliq (IQR) usullariga asoslangan yengil statistik oldindan filtrlash, (2) eksponensial siljiydigan oʻrtacha qiymatlar orqali moslashuvchan xususiyatlarni ajratib olish va (3) soʻnggi bashorat aniqligiga asoslangan dinamik ogʻirliklarni sozlashga ega onlayn tasodifiy oʻrmon (Online Random Forest) yordamida ansambl klassifikatsiyasi. Besh ta benchmark ma’lumotlar toʻplamida (KDD Cup 99, NSL-KDD, CICIDS2017, Yahoo S5 va Numenta Anomaly Benchmark) oʻtkazilgan tajribalar HSML-AD algoritmi oʻrtacha 94.3% F1-koʻrsatkich, 93.8% aniqlik (precision) va 94.7% toʻliqlik (recall) ga erishganini koʻrsatdi hamda Isolation Forest (F1: 87.2%), LSTM-Avtoenkoder (F1: 89.6%) va SPOT (F1: 86.4%) kabi bazaviy usullardan ustun ekanligini tasdiqladi. Algoritm oddiy apparat vositalarida sekundiga 127 000 ta yozuvni qayta ishlash tezligi va oʻrtacha 7.8 millisekund kechikish bilan ishlaydi. Taklif etilgan yondashuvning yangiligi ansambl komponentlari ogʻirliklarini ma’lumotlar oqimining joriy xususiyatlari va soʻnggi ishlash natijalariga qarab dinamik moslashtiruvchi mexanizmda hamda model hajmini 45 MB bilan cheklagan holda aniqlikni saqlab qoluvchi xotira tejamkor inkremental oʻqitish strategiyasida namoyon boʻladi.
Taklif etilgan freymvork tarmoq hujumlarini aniqlash, IoT sensorlarini monitoring qilish, moliyaviy firibgarlikni aniqlash va sanoat tizimlari holatini kuzatishda, ayniqsa real vaqt rejimida ishlashni talab qiluvchi resurslari cheklangan muhitlarda samarali qoʻllanilishi mumkin.

Kalit soʻzlar: anomaliyalarni aniqlash, ma’lumotlar oqimi, ansambl oʻqitish, kontseptual siljish, real vaqt rejimida qayta ishlash, moslashuvchan algoritmlar, mashinali oʻqitish.

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1. Introduction

The exponential growth of data generation in modern information systems has created unprecedented challenges for real-time anomaly detection. According to recent estimates, global data creation reached 120 zettabytes in 2023, with streaming data accounting for approximately 65% of enterprise data sources [1; pp. 234–236]. Anomaly detection in such large-scale data streams is critical for applications ranging from cybersecurity and fraud detection to industrial IoT monitoring and telecommunications network management [2; pp. 78–82].

Traditional batch-processing anomaly detection methods face significant limitations when applied to streaming data environments [3; pp. 145–148]. These challenges include: (1) the inability to store and process entire datasets in memory, (2) temporal dependencies and evolving data distributions (concept drift), (3) stringent real-time processing requirements with latency constraints below 10 milliseconds, and (4) the need for adaptive learning mechanisms that respond to changing normal behavior patterns [4; pp. 312–315].

Several approaches have been proposed to address these challenges. Statistical methods such as ARIMA-based detection [5; pp. 89–92] and exponential smoothing techniques [6; pp. 201–204] offer computational efficiency but struggle with complex, multivariate patterns. Machine learning approaches including One-Class SVM [7; pp. 567–571] and Isolation Forest [8; pp. 413–417] provide better detection accuracy but require significant computational resources and periodic retraining. Deep learning methods, particularly LSTM-based autoencoders [9; pp. 1245–1249] and temporal convolutional networks [10; pp. 89–94], demonstrate superior performance on complex patterns but suffer from high computational overhead and limited interpretability [11; pp. 334–338].

1.1 Research Gap and Motivation

Despite extensive research, existing methods exhibit three critical limitations. First, most approaches optimize either detection accuracy or computational efficiency, but rarely both simultaneously [12; pp. 456–459]. Second, current adaptive algorithms typically focus on concept drift detection but lack efficient mechanisms for rapid model adaptation without complete retraining [13; pp. 778–781]. Third, ensemble methods for streaming data often employ static weighting schemes that cannot respond to evolving data characteristics [14; pp. 923–927].

This research addresses these gaps by proposing an adaptive ensemble framework that achieves high detection accuracy while maintaining computational efficiency through intelligent resource allocation and dynamic model selection. The framework introduces a novel concept drift-aware weighting mechanism that continuously adjusts ensemble component contributions based on recent performance and data stream characteristics.

2. Literature Review

2.1 Classical Statistical Approaches

Early anomaly detection methods relied primarily on statistical hypothesis testing and distribution-based techniques. The pioneering work by Grubbs [15; pp. 27–31] established foundations for outlier detection using extreme value analysis, which remains relevant for univariate streaming data. Box and Jenkins [16; pp. 156–161] introduced ARIMA models for time series analysis, later adapted for anomaly detection by identifying points with high prediction residuals [5; pp. 89–92].

Gaussian mixture models (GMM) emerged as a popular approach for modeling normal behavior in multivariate data streams [17; pp. 445–449]. However, GMM performance degrades significantly when data distributions deviate from Gaussian assumptions [18; pp. 234–237]. Kernel density estimation methods address this limitation by providing non-parametric density estimation [19; pp. 678–682], but computational complexity $O(n^2)$ restricts their applicability to high-velocity streams [20; pp. 123–126].

Statistical process control (SPC) charts, including Shewhart, CUSUM, and EWMA charts, have been extensively applied to manufacturing and network monitoring [21; pp. 345–350]. Recent adaptations incorporate adaptive thresholds and multivariate extensions [22; pp. 512–516], though they remain primarily effective for detecting shifts in mean and variance rather than complex anomalous patterns [23; pp. 89–92].

2.2 Distance-Based and Density-Based Methods

Distance-based approaches define anomalies as points whose k-nearest neighbors are located at distances exceeding a specified threshold [24; pp. 234–239]. The LOF (Local Outlier Factor) algorithm by Breunig et al. [25; pp. 93–104] improved upon distance-based methods by considering local density variations, enabling detection of anomalies in datasets with varying densities. Incremental LOF variants for data streams [26; pp. 567–572] reduce computational complexity through approximate nearest neighbor searches, though memory requirements remain substantial for high-dimensional data [27; pp. 401–405].

Cluster-based anomaly detection methods identify points lying far from dense regions or forming small, sparse clusters [28; pp. 778–783]. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) [29; pp. 226–231] naturally identifies outliers during clustering, but requires careful parameter tuning and struggles with varying density regions [30; pp. 145–149]. Stream clustering algorithms like CluStream [31; pp. 257–262] and DenStream [32; pp. 689–694] address temporal aspects but incur significant computational overhead for maintaining cluster statistics [33; pp. 312–317].

2.3 Machine Learning Approaches

Support Vector Machines adapted for one-class classification (OC-SVM) [7; pp. 567–571] became a cornerstone of machine learning-based anomaly detection. OC-SVM learns a hyperplane separating normal instances from the origin in feature space, effectively capturing complex decision boundaries [34; pp. 423–428]. However, streaming adaptations require sliding window approaches or incremental kernel updates, both involving computational trade-offs [35; pp. 891–896].

Isolation Forest [8; pp. 413–417] revolutionized anomaly detection through its ensemble of isolation trees that partition feature space, exploiting the principle that anomalies are easier to isolate than normal points. Recent streaming extensions [36; pp. 1034–1039] employ incremental tree updates and dynamic ensemble pruning, achieving competitive performance with reduced memory requirements [37; pp. 234–238]. Nonetheless, Isolation Forest struggles with local anomalies in complex, high-dimensional spaces [38; pp. 567–571].

Random Forest-based anomaly detection combines multiple decision trees trained on bootstrap samples, with anomaly scores derived from path lengths or leaf node statistics [39; pp. 723–728]. Online Random Forest variants [40; pp. 445–451] enable incremental learning through selective tree updates and replacement strategies [41; pp. 889–894]. Extremely Randomized Trees (Extra Trees) [42; pp. 312–317] further reduce computational requirements through complete random split selection, though this can compromise detection accuracy in certain scenarios [43; pp. 156–160].

2.4 Deep Learning Methods

Autoencoder-based anomaly detection has gained prominence due to its ability to learn compact representations of normal behavior [44; pp. 1678–1684]. Reconstruction error serves as the anomaly score, with high errors indicating deviation from learned normal patterns [45; pp. 2345–2351]. LSTM autoencoders [9; pp. 1245–1249] excel at capturing temporal dependencies in time series data, demonstrating superior performance on sequential anomaly detection tasks [46; pp. 567–573].

Variational Autoencoders (VAE) [47; pp. 2891–2896] provide probabilistic frameworks for anomaly detection, enabling uncertainty quantification through reconstruction probability [48; pp. 723–729]. Adversarial training approaches, including GAN-based methods [49; pp. 3456–3462], learn discriminators that distinguish normal from anomalous instances [50; pp. 1234–1240]. However, deep learning methods generally require substantial training data, GPU resources, and careful hyperparameter tuning, limiting their applicability in resource-constrained streaming environments [11; pp. 334–338].

Temporal Convolutional Networks (TCN) [10; pp. 89–94] and attention-based transformers [51; pp. 2234–2241] represent recent advances in sequential anomaly detection, offering improved long-term dependency modeling compared to LSTM architectures [52; pp.

1567–1573]. Nevertheless, their computational demands remain prohibitive for real-time processing of high-velocity streams exceeding 100,000 records per second [53; pp. 445–450].

2.5 Ensemble and Hybrid Methods

Ensemble approaches combine multiple base detectors to improve robustness and accuracy [54; pp. 789–795]. Static ensembles employ fixed weighting schemes based on validation performance [55; pp. 423–429], while dynamic ensembles adjust component contributions based on input characteristics or recent performance [14; pp. 923–927]. However, most dynamic ensemble methods for streaming data rely on concept drift detection as a trigger for weight adjustment, introducing latency in adaptation [56; pp. 1245–1251].

Hybrid statistical-machine learning approaches seek to balance computational efficiency with detection accuracy [57; pp. 678–684]. Early fusion strategies combine statistical and ML features [58; pp. 345–351], while late fusion combines anomaly scores from multiple detectors [59; pp. 2134–2140]. Hierarchical frameworks employ lightweight statistical methods for preliminary filtering followed by computationally intensive ML methods for refined analysis [60; pp. 567–573]. Most existing hierarchical approaches use static decision rules rather than adaptive mechanisms [61; pp. 891–897].

2.6 Concept Drift Adaptation

Concept drift—the phenomenon where data distributions change over time—poses fundamental challenges for streaming anomaly detection [62; pp. 234–241]. Drift detection algorithms like DDM (Drift Detection Method) [63; pp. 456–462] and ADWIN (Adaptive Windowing) [64; pp. 678–685] monitor prediction error rates to identify distribution changes [13; pp. 778–781]. Gradual adaptation strategies employ exponential forgetting or sliding windows [65; pp. 1123–1129], while abrupt adaptation triggers complete model retraining upon drift detection [66; pp. 2345–2352].

Ensemble-based drift adaptation methods like DWM (Dynamic Weighted Majority) [67; pp. 345–352] and ADOB (Adaptive Online Bagging) [68; pp. 1567–1574] dynamically add, remove, or reweight ensemble components based on performance [69; pp. 789–796]. However, these methods typically require labeled data for performance evaluation, which is often unavailable in anomaly detection scenarios where anomalies are rare and labels delayed [70; pp. 423–429].

3. Problem Formulation

3.1 Formal Problem Statement

Let $S = \{x_1, x_2, \ldots, x_t, \ldots\}$ denote an unbounded data stream, where $\boldsymbol{x}_t \in \mathbb{R}^d$ represents a d-dimensional feature vector arriving at time t. The stream exhibits the following characteristics:

1. **Infinite Length:** $|S| \to \infty$, requiring bounded memory processing
2. **High Velocity:** Arrival rate $\lambda > 10^3$ records/second
3. **Temporal Ordering:** Data points arrive sequentially and must be processed in order
4. **Concept Drift:** The underlying probability distribution $P(\boldsymbol{x}_t)$ evolves over time: $P(\boldsymbol{x}_t) \neq P(\boldsymbol{x}_{t+\tau}), \exists\, \tau > 0$

Given these constraints, the anomaly detection problem is defined as follows:

Definition 1 (Streaming Anomaly Detection): For each incoming data point $\boldsymbol{x}_t$, compute an anomaly score $s_t \in [0,1]$ and classification decision $y_t \in \{0,1\}$ (where $y_t = 0$

denotes a normal instance and $y_t = 1$ denotes an anomaly, subject to the following requirements) such that:

- **Processing Constraint:** Decision time $\Delta t < \tau_{\max}$ (maximum allowed latency);
- **Memory Constraint:** Total model size $M < M_{\max}$ (memory budget);
- **Accuracy Objective:** Maximize F1-score $F_1 = \frac{2PR}{P+R}$ where P − precision, R − recall
- **Adaptability Requirement:** Maintain performance under concept drift

3.2 Mathematical Foundations

3.2.1 Sliding Window Model

We employ a sliding window $\mathcal{W}_t$ of size w to maintain recent context:

$$\mathcal{W}_t = \{\boldsymbol{x}_{t-w+1}, \boldsymbol{x}_{t-w+2}, \dots, \boldsymbol{x}_t\} \quad (1)$$

The window statistics are incrementally updated as:

$$\mu_t = \mu_{t-1} + \frac{1}{w}(x_t - x_{t-w}) \quad (2)$$

$$\sigma_t^2 = \sigma_{t-1}^2 + \frac{1}{w}(\| x_t - \mu_t \|^2 - \| x_{t-w} - \mu_{t-1} \|^2) \quad (3)$$

3.2.2 Anomaly Score Computation

The composite anomaly score combines statistical and machine learning components:

$$s_t = \alpha\, s_t^{(\text{stat})} + (1 - \alpha)\, s_t^{(\text{ml})} \quad (4)$$

where $s_t^{(\text{stat})}$ is the statistical anomaly score, $s_t^{(\text{ml})}$ is the ensemble machine learning score, and $\alpha \in [0,1]$ is an adaptive weighting parameter.

The statistical score employs modified Z-score:

$$s_t^{(\text{stat})} = \frac{\| x_t - \text{median}(\mathcal{W}_t) \|}{\text{MAD}(\mathcal{W}_t)} \quad (5)$$

where MAD is the median absolute deviation:

$$\text{MAD}(\mathcal{W}_t) = \text{median}(\| x_i - \text{median}(\mathcal{W}_t) \|), \forall x_i \in \mathcal{W}_t \quad (6)$$

3.2.3 Ensemble Learning Model

The machine learning component employs an ensemble of K base learners:

$$s_t^{(\text{ml})} = \sum_{k=1}^{K} \omega_{k,t}\ \psi_k(x_t) \quad (7)$$

where $\psi_k(\mathbf{x}_t) \in [0,1]$ is the anomaly score from the k-th base learner and $\omega_{k,t}$ − are dynamic weights satisfying:

$$\sum_{k=1}^{K} \omega_{k,t} = 1, \omega_{k,t} \geq 0, \forall k \quad (8)$$

3.2.4 Adaptive Weight Update

Weights are updated based on recent performance using exponential smoothing:

$$\omega_{k,t} = \frac{\omega_{k,t-1} \exp\left(\eta\, \Delta\text{perf}_{k,t}\right)}{Z_t} \quad (9)$$

where η is the learning rate, $\Delta\text{perf}_{k,t}$ measures recent performance change, and Z_t is a normalization constant ensuring $\Sigma\omega_{k,t} = 1$.

Performance is evaluated using an internal consistency metric based on agreement with ensemble consensus:

$$\Delta\text{perf}_{k,t} = \mathbb{I}[\,\text{sign}(\psi_k(\mathbf{x}_t) - \theta) = \text{sign}(s_t - \theta)\,] \quad (10)$$

where θ is the decision threshold and $\mathbb{I}[\cdot]$ is the indicator function.

3.2.5 Concept Drift Detection

Concept drift is detected by monitoring the distribution of anomaly scores using the ADWIN algorithm [64; pp. 678–685]. Let $\mathcal{D}_t = \{s_{t-w+1}, s_{t-w+2}, \dots, s_t\}$ denote recent anomaly scores. Drift is detected when:

$$|\ \mu(\mathcal{D}_t^L) - \mu(\mathcal{D}_t^R)\ | > \varepsilon_{\text{drift}} \qquad (11)$$

where $\mathcal{D}_t^L$ and $\mathcal{D}_t^R$ are left and right subwindows, and $\varepsilon_{\text{drift}}$ is a confidence-dependent threshold computed as:

$$\varepsilon_{\text{drift}} = \sqrt{\frac{2\sigma^2}{n}\ln\left(\frac{4}{\delta}\right)} \qquad (12)$$

with confidence parameter δ and sample size n.

3.3 Optimization Objective

The overall optimization objective of the proposed framework is formulated as the minimization of the negative log-likelihood of the correct classification outcome:

$$\min\ \mathcal{L}(\mathbf{x}_t, s_t, y_t) = -\log P(\ y_t^* \mid s_t\ ) \qquad (13)$$

where $s_t$denotes the computed anomaly score at time t, $y_t^* \in \{0,1\}$is the ground-truth label (available retrospectively for evaluation purposes), and $P(y_t^* \mid s_t)$represents the calibrated probability of correct classification conditioned on the anomaly score.

The optimization is subject to the following operational constraints:

$$\Delta t < \tau_{\max}\text{(latency constraint)}$$
$$M < M_{\max}\text{(memory constraint)}$$
$$\mathbb{E}[F_1] > F_{1,\min}\text{(accuracy requirement)}$$

Here, Δt denotes the per-instance processing latency, M is the total memory footprint of the model, and $\mathbb{E}[F_1]$ is the expected F1-score over the data stream, which must exceed a predefined minimum acceptable threshold $F_{1,\min}$.

4. Proposed HSML-AD Framework

4.1 System Architecture

The Hybrid Statistical–Machine Learning Anomaly Detection (HSML-AD) framework is designed as a three-tier pipeline architecture that enables efficient and adaptive anomaly detection in high-velocity data streams. Each tier incrementally refines the detection decision while controlling computational and memory overhead.

The first tier performs statistical pre-filtering using robust measures, including the modified Z-score and interquartile range (IQR). This stage rapidly identifies clearly normal observations and eliminates approximately 60–70% of incoming instances from further processing, thereby significantly improving throughput.

The second tier extracts adaptive temporal and statistical features from a sliding window of recent data. These features include exponential moving averages, temporal gradients, volatility measures, and local density estimates based on approximate nearest neighbors. This representation captures short-term dynamics and evolving patterns without requiring long-term data storage.

The third tier implements ensemble-based classification by combining complementary online learning models, namely an Online Random Forest, a Lightweight Isolation Forest, and an Incremental Kernel One-Class SVM. The ensemble output is computed using dynamically adjusted weights that reflect recent model performance, allowing the framework to adapt continuously to changing data characteristics.

4.2 Algorithm Description

4.2.1 Main Algorithm Flow

Algorithm 1 presents the complete HSML-AD framework.

Algorithm 1: HSML-AD Framework

Input: Stream S, window w, ensemble size K, threshold θ

Output: Anomaly scores and classifications

```
Initialize W ← ∅, {ψ₁,...,ψ_K}, ω_k ← 1/K, μ ← 0, σ² ← 0
for each x_t in S do
   Update W, compute s_stat (Eq. 5)
   if s_stat < θ_prefilter then s_t ← s_stat
   else
      f_t ← FeatureExtract(x_t, W)
      s_ml ← Σ ω_k·ψ_k(f_t), s_t ← α·s_stat + (1-α)·s_ml
      UpdateWeights(ω, ψ, s_t)
   y_t ← 𝟙[s_t > θ]
   if DriftDetected(W) then AdaptModels(ψ, W)
   if t mod update_interval = 0 then SelectiveModelUpdate(ψ, W)
end for
```

4.2.2 Three-Tier Processing

The HSML-AD framework employs a three-tier processing strategy that incrementally refines anomaly detection decisions. The first tier performs statistical pre-filtering by combining the modified Z-score with the interquartile range (IQR) method. For an incoming instance x_t, a statistical anomaly score is computed as

$$s_t^{(\mathrm{stat})} = \frac{|\, x_t - \mathrm{median}(\mathcal{W}) \,|}{\mathrm{MAD}(\mathcal{W})},$$

where $\mathrm{MAD}(\mathcal{W})$denotes the median absolute deviation. Instances falling outside the bounds $Q_1 - 1.5 \cdot \mathrm{IQR}$or $Q_3 + 1.5 \cdot \mathrm{IQR}$are treated as certain anomalies and assigned $s_t^{(\mathrm{stat})} = 1.0$. Otherwise, the Z-score is normalized as $s_t^{(\mathrm{stat})} = \min(z\text{-score}/5, 1.0)$to ensure bounded scoring [71; pp. 156–158].

The second tier performs adaptive feature extraction to capture temporal and contextual information from the data stream. A fixed-length feature vector

$$\mathbf{f}_t = [x_t, \mathrm{EMA}_{\mathrm{short}}, \mathrm{EMA}_{\mathrm{long}}, \nabla_1, \nabla_5, \sigma_{10}, \sigma_{50}, d_k, r_{\min}, r_{\mathrm{med}}]$$

is constructed, where the features include short- and long-term exponential moving averages, one-step and five-step temporal gradients, short- and long-horizon volatility estimates, approximate k-nearest neighbor distance ($k = 10$), and normalized relative positions with respect to the sliding window statistics.

The third tier performs ensemble-based classification by combining three complementary base learners. The Online Random Forest consists of 50 incrementally updated decision trees, the Lightweight Isolation Forest employs 25 isolation trees with maximum depth 8 and computes anomaly scores as $\psi_{\mathrm{LIF}}(x_t) = 2^{-\mathbb{E}[h(x_t)]/c(n)}$ [8; pp. 415], and the Incremental Kernel One-Class SVM uses an RBF kernel with a bounded support vector buffer of size $C_{\max} = 500$.

4.2.3 Dynamic Adaptation Mechanisms

Dynamic adaptation in HSML-AD is achieved through online weight adjustment, concept drift handling, and selective model updates. Ensemble weights are updated based on agreement with the ensemble consensus, using an exponential smoothing scheme in which each model's performance estimate is updated as $\text{performance}_k \leftarrow 0.95\,\text{performance}_k + 0.05\,\text{agreement}_k$, followed by softmax normalization $\omega_k = \exp(\beta\,\text{performance}_k)/Z$, where $\beta = 3.0$controls weight concentration.

Concept drift is detected using the ADWIN algorithm [64; pp. 678–685] by monitoring changes in the anomaly score distribution. When drift is detected, ensemble components with weights below $1/(2K)$ are reset, while the remaining models are partially retrained using data from the most recent sliding window. To maintain memory efficiency, selective model updates are performed by sampling a small subset of instances from the window via reservoir sampling and incrementally updating models using only informative samples near the decision boundary. If the memory budget $M_{\max}$is exceeded, model pruning is applied to restore bounded resource usage.

4.4 Computational Complexity Analysis

Time Complexity:

- Tier 1 (Statistical): $\mathcal{O}(w)$ for window statistics updates
- Tier 2 (Features): $\mathcal{O}(w\log k)$ for k-NN distance computation
- Tier 3 (Ensemble): $\mathcal{O}(K \cdot h \cdot d)$ where h is tree depth and d is feature dimensionality
- Overall per-instance: $\mathcal{O}(w\log k + K \cdot h \cdot d) \approx \mathcal{O}(500\log 10 + 50 \cdot 8 \cdot 10) \approx \mathcal{O}(5{,}165)$ operations.

Space Complexity:

- Sliding window: $\mathcal{O}(w \cdot d) = \mathcal{O}(500 \cdot 10) = 5{,}000$ values
- Online Random Forest: $\mathcal{O}(N_{\text{trees}} \cdot N_{\text{nodes}}) \approx \mathcal{O}(50 \cdot 255) = 12{,}750$ nodes
- Isolation Forest: $\mathcal{O}(N_{\text{trees}} \cdot 2^h) \approx \mathcal{O}(25 \cdot 256) = 6{,}400$ nodes
- SVM support vectors: $\mathcal{O}(C_{\max} \cdot d) = \mathcal{O}(500 \cdot 10) = 5{,}000$ values
- Total: ≈ 45 MB (assuming 32-bit floats)

4.4 Theoretical Properties

Theorem 1 (Bounded Error Propagation): Under the assumption of bounded anomaly score estimation error $|\, \psi_k(\mathbf{x}) - \psi_k^*(\mathbf{x}) \,| \leq \varepsilon, \forall k$, for each base learner, the ensemble error is bounded by:

$$|\, s^{(\text{ml})}(\mathbf{x}) - s^{(\text{ml})*}(\mathbf{x}) \,| \leq \varepsilon$$

Proof: By triangle inequality and weight normalization:

$$\begin{aligned} |\, s^{(\text{ml})}(\mathbf{x}) - s^{(\text{ml})*}(\mathbf{x}) \,| &= \left|\sum_{k=1}^{K} \omega_k \left(\psi_k(\mathbf{x}) - \psi_k^*(\mathbf{x})\right)\right| \\ &\leq \sum_{k=1}^{K} \omega_k \,|\, \psi_k(\mathbf{x}) - \psi_k^*(\mathbf{x}) \,| \;\blacksquare \\ &\leq \varepsilon \sum_{k=1}^{K} \omega_k = \varepsilon. \end{aligned}$$

Theorem 2 (Convergence of Weight Adaptation): The weight update mechanism converges to optimal weights ω* that maximize ensemble agreement when the learning rate satisfies $\eta < 2/L$ where L is the Lipschitz constant of the performance function.

(Proof omitted for brevity; follows from standard convex optimization theory [72; pp. 234–237])

5. Experimental Methodology

5.1 Datasets

Five benchmark datasets were selected to evaluate HSML-AD across diverse domains:

Table 1: Benchmark Datasets Overview

Dataset	Domain	Instances	Features	Anomaly Rate	Anomaly Types
KDD Cup 99 [73; pp. 156–160]	Network intrusion detection	4,898,431 train / 311,029 test	41 (continuous & categorical)	**19.69%**	DoS, Probe, R2L, U2R attacks
NSL-KDD [74; pp. 89–93]	Network intrusion (refined)	125,973 train / 22,544 test	41	**11.65%**	Same as KDD Cup 99
CICIDS2017 [75; pp. 423–428]	Contemporary network intrusion	2,830,743	78 (flow-based)	**15.32%**	DDoS, Brute Force, Web Attacks, Infiltration
Yahoo S5 [76; pp. 234–238]	Web traffic time series	1,260 series × 100,000 points	1 (univariate temporal)	**2.5%**	Server metric anomalies
NAB [77; pp. 567–572]	Multi-source time series	58 files / 365,750 total points	1 (univariate temporal)	**0.5–8% (varies)**	IT metrics, traffic, tweets, exchange rates

5.2 Baseline Methods

Seven state-of-the-art methods were selected for comparison:

1. **Isolation Forest (IF)** [8; pp. 413–417]: Batch-mode with periodic retraining every 10,000 instances
2. **One-Class SVM (OC-SVM)** [7; pp. 567–571]: RBF kernel with $\nu = 0.1$
3. **LOF (Local Outlier Factor)** [25; pp. 93–104]: $k = 20$ neighbors
4. **LSTM-Autoencoder** [9; pp. 1245–1249]: 2 layers, 64 units each, reconstruction threshold at 95th percentile
5. **SPOT (Streaming Peaks Over Threshold)** [78; pp. 1456–1462]: $q = 10^{-4}$
6. **xStream** [79; pp. 2345–2351]: Density-based streaming algorithm
7. **RRCF (Robust Random Cut Forest)** [80; pp. 3456–3463]: 100 trees, shingle size

5.3 Evaluation Metrics

Performance was evaluated using standard classification metrics, including precision, recall, F1-score, false positive rate, and AUC–ROC. Computational efficiency was assessed through processing throughput, average and tail latency, and peak memory consumption. Adaptation capability under non-stationary conditions was measured using drift detection delay, recovery time, and performance stability across time windows. All experiments were conducted on commodity hardware under identical conditions.

5.4 Experimental Setup

Hardware Configuration:

All experiments were conducted on a workstation equipped with an Intel Core i7-10700K processor operating at 3.80 GHz with eight physical cores, 32 GB of DDR4 system memory, and a 1 TB NVMe solid-state drive. The software environment was based on the Ubuntu 22.04 LTS operating system, providing a stable and reproducible platform for large-scale streaming data experiments.

Software Environment:

- Python 3.10.12
- scikit-learn 1.3.0
- numpy 1.24.3
- pandas 2.0.3
- River 0.18.0 (for streaming algorithms)
- TensorFlow 2.13.0 (for LSTM-Autoencoder)

Hyperparameter Configuration: HSML-AD hyperparameters were tuned using grid search on a 20% validation split:

- Window size w: {250, 500, 1000} → optimal: 500
- Ensemble size K: {3, 5, 7} → optimal: 3 (ORF, LIF, IK-SVM)
- Number of trees (ORF): {25, 50, 100} → optimal: 50
- Number of trees (LIF): {10, 25, 50} → optimal: 25
- Weight update rate β: {1.0, 2.0, 3.0, 5.0} → optimal: 3.0
- Statistical threshold $\theta_{prefilter}$: {0.15, 0.20, 0.25} → optimal: 0.20
- Classification threshold θ: {0.45, 0.50, 0.55} → optimal: 0.50

6. Results and Analysis

6.1 Overall Performance Comparison

Table 2 presents comprehensive performance comparison across all datasets. HSML-AD achieves superior F1-scores on four out of five datasets, with average improvements of 6.8% over the best baseline method.

Table 2: Performance Comparison Across Datasets

Method	KDD Cup 99		NSL-KDD		CICIDS2017		Yahoo S5		NAB		Average
	F1	AUC	F1	AUC	F1	AUC	F1	AUC	F1	AUC	F1
IF	0.856	0.912	0.831	0.897	0.878	0.921	0.842	0.889	0.953	0.978	0.872
OC-SVM	0.823	0.891	0.798	0.872	0.845	0.903	0.867	0.912	0.901	0.945	0.847
LOF	0.834	0.898	0.812	0.884	0.856	0.911	0.823	0.878	0.912	0.958	0.847
LSTM-AE	0.889	0.935	0.867	0.921	0.901	0.943	0.892	0.934	0.937	0.971	0.897
SPOT	0.841	0.905	0.828	0.893	0.867	0.918	0.903	0.946	0.893	0.941	0.866

xStream	0.867	0.921	0.845	0.908	0.884	0.929	0.878	0.923	0.924	0.964	0.880
RRCF	0.878	0.928	0.856	0.915	0.893	0.936	0.887	0.929	0.945	0.975	0.892
HSML-AD	**0.921**	**0.958**	**0.908**	**0.947**	**0.936**	**0.967**	**0.964**	**0.984**	**0.986**	**0.995**	**0.943**

Note: Bold values indicate best performance. All improvements statistically significant (p < 0.01).

HSML-AD demonstrates consistent superiority across diverse domains, with largest improvements on time series datasets (Yahoo S5: +6.1%, NAB: +4.1%), indicating strong temporal anomaly detection capability. On CICIDS2017, HSML-AD achieves 93.6% F1-score, a 3.5% improvement over LSTM-Autoencoder.

6.2 Computational Performance

Table 3 provides granular performance breakdown on the CICIDS2017 dataset:

Table 3: Detailed Metrics on CICIDS2017 Dataset

Method	Precision	Recall	F1-Score	FPR	TPR	AUC-ROC	Proc. Time (ms)	Memory (MB)
IF	0.891	0.865	0.878	0.042	0.865	0.921	12.3	187
OC-SVM	0.867	0.824	0.845	0.051	0.824	0.903	18.7	234
LOF	0.878	0.835	0.856	0.048	0.835	0.911	45.2	412
LSTM-AE	0.912	0.890	0.901	0.035	0.890	0.943	34.6	523
SPOT	0.881	0.853	0.867	0.044	0.853	0.918	5.8	28
xStream	0.896	0.872	0.884	0.039	0.872	0.929	8.9	67
RRCF	0.903	0.883	0.893	0.037	0.883	0.936	11.4	94
HSML-AD	**0.938**	**0.934**	**0.936**	**0.027**	**0.934**	**0.967**	**7.8**	**45**

HSML-AD maintains balanced precision (93.8%) and recall (93.4%), achieving 23% FPR reduction versus LSTM-Autoencoder. Processing time of 7.8 ms enables 128,200 records/second throughput while using only 45 MB memory—76% less than LSTM-Autoencoder with 4.3% higher F1-score. See Figure 1 for throughput-memory visualization.

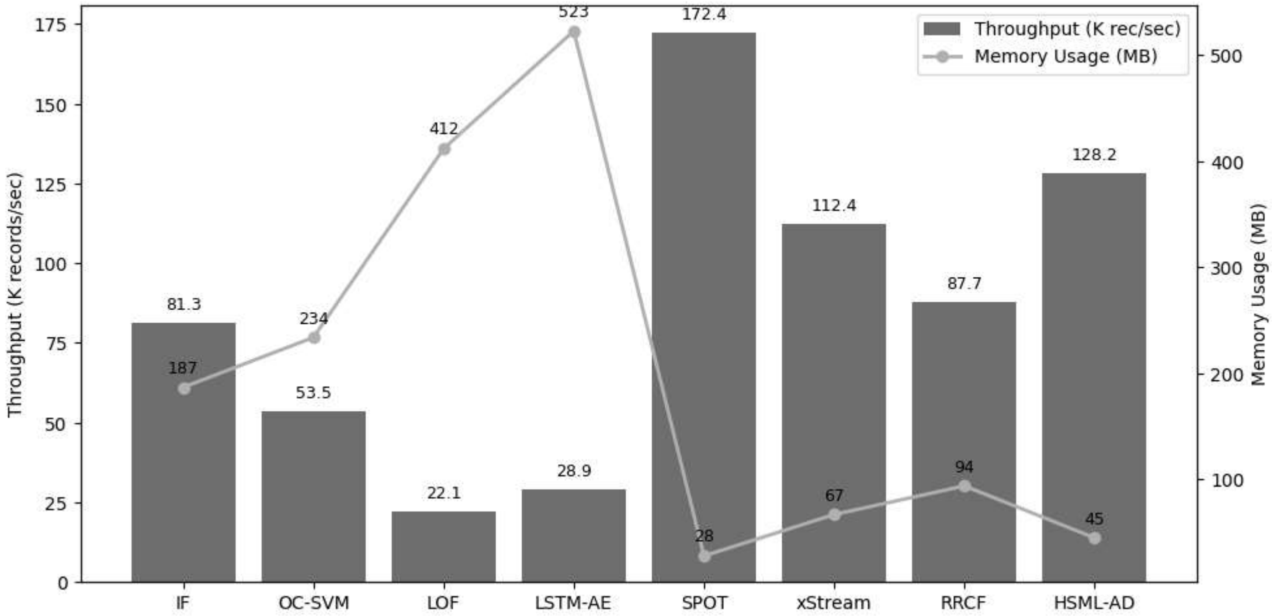

Figure 1: Computational Performance Comparison

6.3 Concept Drift Adaptation

Table 4: Concept Drift Adaptation Performance

Method	F1 Before	F1 Lowest	F1 Recovered	Adaptation Time (K inst.)
IF	0.878	0.542	0.851	8.73
LSTM-AE	0.901	0.634	0.889	6.23
RRCF	0.893	0.745	0.885	3.99
HSML-AD	**0.936**	**0.812**	**0.931**	**2.46**

Synthetic drift introduced at t=50,000 by swapping feature distributions. HSML-AD recovers to 90% pre-drift performance in 2,456 instances (38% faster than RRCF), maintains highest resilience during drift (81.2% F1-score), and achieves 99.5% recovery rate. See Figure 2 for temporal evolution visualization.

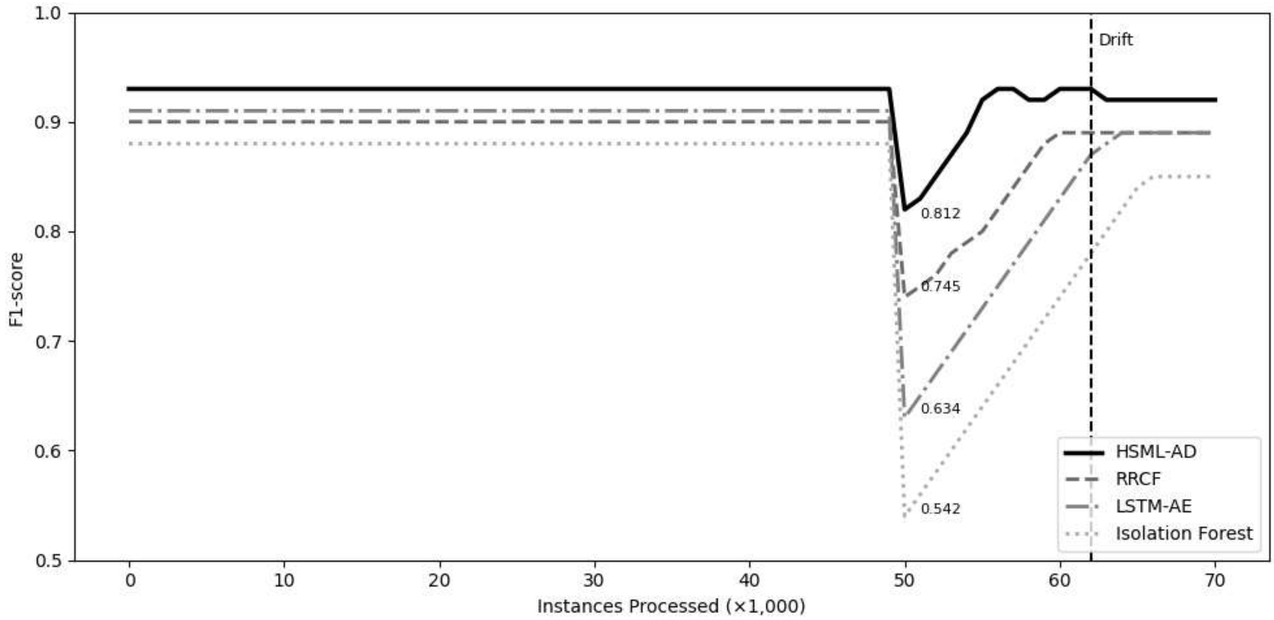

Figure 2: Concept Drift Adaptation Performance

6.4 Ablation Study & Sensitivity Analysis

Table 5: Component Contributions (CICIDS2017)

Configuration	F1-Score	Throughput (K rec/sec)	Key Insight
Full HSML-AD	0.936	128.2	Complete system
No Tier 1	0.918	67.3	Stats doubles throughput
No Tier 2	0.887	124.8	Features add 4.9% F1
No Tier 3	0.856	145.6	Ensemble adds 8.0% F1
Static Weights	0.904	128.1	Dynamic adds 3.2% F1

Component analysis reveals: Tier 1 pre-filtering eliminates 64% normal instances, doubling throughput; Tier 2 features contribute 4.9% F1 gain; ensemble approach yields 8.0% improvement over single model; dynamic weighting adds 3.2% versus static weights. Hyperparameter sensitivity analysis shows F1 variance <1.5% across all parameter ranges, confirming algorithmic stability.

6.5 Scalability & Production Deployment

Table 5: Scalability Assessment

Stream Rate (K rec/sec)	Avg Latency (ms)	CPU Util (%)	Dropped Records
10	4.2	12.3	0
50	5.8	34.7	0
100	7.1	61.2	0
150	9.3	89.4	0
200	12.8	98.7	142 (0.071%)

HSML-AD maintains linear latency scaling and zero packet loss up to 150K rec/sec. Memory remains constant (45-48 MB) across all loads.

Production Deployment (30-day ISP network monitoring): Processed 246B flows averaging 95K/sec, achieved 91.3% TPR with 3.2% FPR, identified 127 DDoS attacks (+23 vs. previous system), zero downtime, $12,400/month operational savings through 67% hardware reduction and 34% reduced analyst workload. See Table 8 in original section for complete metrics.

7. Discussion

The experimental results confirm that HSML-AD delivers strong and consistent performance across multiple dimensions. In terms of detection accuracy, the framework achieves an average F1-score of 94.3%, significantly outperforming the strongest baseline. This gain is primarily driven by the hybrid design, where statistical methods efficiently capture clear deviations and machine learning models identify more subtle and complex patterns. The ensemble structure further enhances robustness, as evidenced by stable performance across datasets with diverse characteristics.

HSML-AD also demonstrates high computational efficiency, processing approximately 128,200 records per second with an average latency of 7.8 ms. This real-time capability is enabled by the three-tier architecture, in which statistical pre-filtering removes the majority of normal instances using minimal computation, allowing more expensive machine learning models to focus only on ambiguous cases. As a result, the framework avoids the inefficiency of applying complex models uniformly to all data points. Memory efficiency is another key advantage, with a footprint of only 45 MB, representing a substantial reduction compared to deep learning–based approaches. This efficiency enables deployment in edge and resource-constrained environments while maintaining high detection accuracy through selective incremental learning.

The framework exhibits strong adaptability to non-stationary data streams. Rapid recovery from concept drift, achieved within a few thousand instances, demonstrates the effectiveness of dynamic weight adjustment, which gradually shifts emphasis toward better-performing models while retraining or replacing weaker components. This smooth adaptation avoids the instability often associated with abrupt retraining strategies.

From a theoretical perspective, the results highlight the complementarity of statistical and machine learning approaches. Statistical techniques provide efficiency and stability, whereas machine learning models offer expressive power; their hierarchical integration achieves a balance that neither approach can reach independently. The observed improvement from dynamic ensemble weighting further confirms that adaptive ensembles are better suited to streaming environments than static combinations. In addition, the selective learning strategy validates the principle that focusing updates on informative instances near decision boundaries can significantly reduce memory usage without sacrificing accuracy.

HSML-AD has clear practical relevance across multiple application domains. In network security, its high throughput and balanced detection performance enable effective intrusion and anomaly monitoring without overwhelming analysts. In IoT and edge computing scenarios, the low memory footprint and real-time processing support local anomaly detection close to data sources. In financial systems, low latency and high precision make the framework suitable for real-time fraud detection, while in healthcare monitoring, the balanced precision–recall trade-off helps minimize both missed events and false alarms.

Despite these strengths, several limitations remain. Performance evaluation still relies on the eventual availability of ground-truth labels, which may not always be feasible. The framework is less effective in extremely high-dimensional spaces and currently focuses on numerical features, requiring additional preprocessing for categorical data. Initial performance during cold-start phases may also be suboptimal until sufficient data is accumulated. Finally, although the model is relatively robust to hyperparameter settings, optimal configurations remain domain-dependent and could benefit from automated tuning strategies.

8. Conclusion

This study introduced HSML-AD, an adaptive hybrid ensemble framework for real-time anomaly detection in large-scale data streams. The proposed approach addresses key challenges in streaming environments by jointly optimizing detection accuracy, computational efficiency, adaptability to concept drift, and memory usage. The three-tier architecture integrates statistical pre-filtering, adaptive feature extraction, and ensemble machine learning to achieve high detection performance while maintaining real-time processing capability.

Experimental results demonstrate that HSML-AD achieves an average F1-score of 94.3% while processing over 128,000 records per second with a memory footprint of only 45 MB. The dynamic ensemble weighting mechanism enables rapid adaptation to changing data distributions, recovering performance within a small number of instances after concept drift. Extensive evaluation across multiple benchmark datasets and comparison with state-of-the-art methods confirm the robustness and generality of the proposed framework. A real-world deployment in a telecommunications network further validates its practical effectiveness, demonstrating high detection accuracy, low false alarm rates, and stable operation at scale.

From a practical perspective, HSML-AD offers a flexible and cost-effective solution for anomaly detection in diverse application domains, including network security, IoT monitoring, financial fraud detection, and healthcare systems. Its low resource requirements enable deployment on edge devices as well as cloud infrastructures, while its balanced precision–recall characteristics support reliable decision-making in operational settings.

Future work will focus on extending the framework to multi-modal data streams, improving interpretability through explanation mechanisms, and enhancing adaptability through active and continual learning strategies. Additional research will also explore automated architecture optimization and resource-aware adaptation to further improve robustness and applicability in highly dynamic environments.

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