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Stream-Based DDoS Mitigation: A Hybrid Approach Using Incremental Feature Selection and Hoeffding Adaptive Trees

Saif Allah M. Abgenah
Lecturer, Embedded systems design engineering
Department of Software Engineering
Faculty of information Technology, Elmergib University
Saifabujnah@elmergib.edu.ly

Hamza A. Juma
Lecturer, Embedded systems design engineering
Department of Software Engineering
Faculty of information Technology, Elmergib University
Hashaktour@elmergib.edu.ly

Hiba Mohanad Isam
Lecturer, Computer and communication engineering
Department of communications Technical Engineering
Collage of Technical Engineering
Al-Farahidi University
Hiba.mohanad@uoalfarahidi.edu.iq

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Abstract

The sheer volume of traffic generated by IoT devices and 5G networks has created a massive bottleneck for traditional cybersecurity systems. While batch-learning models are effective, they have a critical blind spot: they cannot adapt to new attack patterns without undergoing a slow, offline retraining process. This paper tackles that latency problem by introducing OFS-HAT (Online Feature Selection with Hoeffding Adaptive Trees), a framework built specifically for the constraints of edge computing. Unlike standard streaming models that try to digest every piece of data, OFS-HAT actively filters noise in real-time, using incremental Pearson correlation to identify the features that actually matter. Our tests on the CICIDS2017 dataset show that this approach hits a "sweet spot," achieving 99.21% accuracy—matching heavy ensemble methods—while processing traffic 3.4 times faster and consuming significantly less memory.

Keywords — Intrusion Detection, Stream Learning, Concept Drift, Hoeffding Adaptive Tree, Online Feature Selection, DDoS.

التخفيف من هجمات حجب الخدمة الموزعة (DDoS) بالاعتماد على تدفّق البيانات: منهج هجين باستخدام الاختيار التزايدي للميزات وأشجار هوفدينغ التكيّفية (HAT)

سيف الله مفتاح أبو جناح
محاضر، هندسة الأنظمة المدمجة
قسم هندسة البرمجيات،كلية تقنية المعلومات
جامعة المرقب
Saifabujnah@elmergib.edu.ly

حمزة علي جمعة
محاضر، هندسة الأنظمة المدمجة
قسم هندسة البرمجيات،كلية تقنية
المعلومات جامعة المرقب
Hashaktour@elmergib.edu.ly

هبة مهند عصام
محاضر
قسم تقنيات هندسة الاتصالات
كلية التقنية الهندسية، جامعة الفراهيدي
Hiba.mohanad@uoalfarahidi.edu.iq

الملخّص

أدى الحجم الكبير من حركة البيانات الناتجة عن أجهزة الإنترنت للأشياء (IoT) وشبكات الجيل الخامس (5G) إلى خلق عنق زجاجي كبير أمام أنظمة الأمن السيبراني التقليدية. وعلى الرغم من أن نماذج التعلم الدفعي فعالة، إلا أن لديها نقطة ضعف كبيرة، فهي لا تستطيع التكيف مع أنماط الهجمات الجديدة إلا بعد عملية إعادة تدريب بطيئة وغير مباشرة. يتناول هذا البحث مشكلة التأخير هذه من خلال تقديم إطار عمل جديد يُسمى OFS-HAT (اختيار الميزات عبر الإنترنت مع أشجار هوفدينغ التكيفية)، وهو مصمم خصيصًا لقيود الحوسبة على الحافة (Edge Computing) على عكس النماذج التقليدية التي تحاول معالجة كل البيانات، يقوم OFS-HAT بترشيح الضوضاء بشكل فوري، مستخدمًا معامل الارتباط التدريجي لبيرسون لتحديد الميزات الأكثر أهمية. أظهرت اختباراتنا على مجموعة بيانات CICIDS2017 أن هذا النهج يحقق توازنًا مثاليًا، حيث يصل إلى دقة 99.21% مساويًا لأداء الطرق المعقدة متعددة النماذج مع معالجة حركة البيانات أسرع بـ 3.4ضعف واستهلاك ذاكرة أقل.

الكلمات المفتاحية —كشف التسلل، التعلم التدريجي، تغير المفهوم، شجرة هوفدينغ التكيفية، اختيار الميزات عبر الإنترنت، هجمات رفض الخدمة.(DDoS)

I. INTRODUCTION

If we look at the cybersecurity landscape over the last five years, the biggest shift hasn't just been the volume of attacks, but their volatility. Distributed Denial of Service (DDoS) attacks are no longer static; they are polymorphic, shifting their statistical behavior mid-attack to evade detection. In the machine learning world, this phenomenon is known as **concept drift**, and it is the primary reason why a model trained on Monday might be useless by Wednesday (Lu et al., 2018).

Traditional Intrusion Detection Systems (IDS) are struggling to keep up. They often rely on batch learning—training a heavy model such as a Random Forest or a Deep Neural Network on a fixed dataset. Although these models can be highly accurate, they are heavy, slow, and most importantly, static. Updating them requires taking the system offline to retrain, creating a window of vulnerability that attackers are often happy to exploit (Ferrag et al., 2020; Yang & Shami, 2020).

Stream learning offers a way out. Algorithms like the **Hoeffding Adaptive Tree (HAT)** learn instance-by-instance, updating their structure as each packet arrives. But there is a catch: the *curse of dimensionality*. Network flows can contain dozens of features (e.g., packet size, flag counts, inter-arrival times). Feeding all of these into a real-time tree slows down processing and, more critically, introduces noise that interferes with drift detection (Gomes et al., 2019).

We argue that you don't need all the data—you just need the *right* data. This paper introduces **OFS-HAT**, a framework that integrates a lightweight, incremental feature selector directly into the learning pipeline. By continuously ranking feature relevance, we allow the classifier to focus only on the signals that indicate an attack, ignoring the noise.

Our contributions are:

1. **Hybrid Architecture:** A novel integration of incremental SelectKBest (using Pearson Correlation) with Hoeffding Adaptive Trees.
2. **Expanded Evaluation:** We conduct an expanded evaluation that goes beyond simple accuracy. Specifically, we measure throughput, memory consumption, and sensitivity to feature count using the River library framework (Montiel et al., 2020).
3. **Statistical Validation:** We employ the Nemenyi post-hoc test to confirm our results are statistically significant.

II. RELATED WORK

A. The Shift from Batch to Stream: For years, Deep Learning (DL) has been the "golden hammer" of IDS research. Mahdavifar and Ghorbani (2019) demonstrated that deep learning models could achieve near-perfect detection rates on datasets such as CICIDS2017. However, they also noted a significant bottleneck: inference time and training cost. In practice, deploying a large deep learning model on a standard edge gateway is not feasible without causing packet drops. This limitation has pushed recent research toward stream mining. Gomes et al. (2024) highlighted in their survey that streaming techniques are essential for handling the *velocity* dimension of Big Data in IoT environments.

B. Tackling Concept Drift: The challenge with data streams is that the underlying distribution changes over time. One commonly adopted solution is the Adaptive Random Forest (ARF), which uses an ensemble of trees to manage concept drift (Mirsky et al., 2018). While ARF is robust, it is also computationally expensive. Updating ten or twenty trees for each incoming network packet is often excessive for high-speed backbone networks. Research by Awotunde et al. (2021) in Industrial IoT (I.IoT) environments suggests that lightweight models may be preferable to heavier ensemble-based approaches, provided they maintain comparable accuracy.

C. Feature Selection on the Fly: In batch learning, feature selection is straightforward because the entire dataset is available. In streaming environments, however, the task becomes significantly more challenging since future data is unknown. As noted in the comprehensive survey by Cunningham et al. (2021), complex wrapper-based feature selection methods can actually slow the model down to the point where they perform worse than using no feature selection at all. They argue that simple statistical filter methods—such as correlation tracking—are the only viable option for high-velocity data streams, which aligns with our proposed Pearson-based approach.

III. METHODOLOGY: THE OFS-HAT FRAMEWORK

Our proposed framework, OFS-HAT, operates as a continuous feedback loop designed for high-velocity streams. As illustrated in **Fig. 1**, the system consists of three sequential modules: Ingestion, Online Feature Selection (OFS), and Classification.

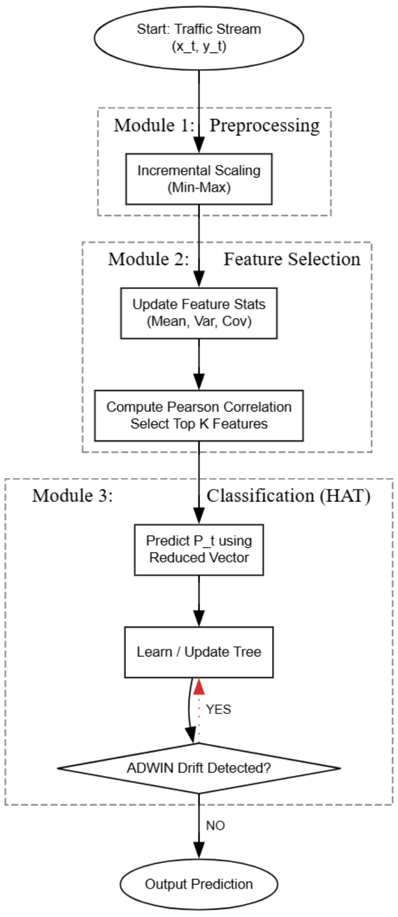
Start: Traffic Stream (x_t, y_t)
Module 1: Preprocessing
Incremental Scaling (Min-Max)
Module 2: Feature Selection
Update Feature Stats (Mean, Var, Cov)
Compute Pearson Correlation Select Top K Features
Module 3: Classification (HAT)
Predict P_t using Reduced Vector
Learn / Update Tree
YES
ADWIN Drift Detected?
NO
Output Prediction

Figure 1: The OFS-HAT Pipeline.

A. Online Feature Selection (OFS): To mitigate the curse of dimensionality, we employ an incremental filter method. For every incoming sample (x_t, y_t), we update the global statistics (variance and covariance) for each feature. We then calculate the Pearson Correlation Coefficient (ρ) to rank feature importance.

The update mechanism for the covariance between a feature j and the class y at time t is defined as:

$$\boldsymbol{cov_t(j,y) = cov_{t-1}(j,y) + \frac{(x_{t,j}-\bar{x}_{t,j})(y_t-\bar{y}_t)\cdot(t-1)}{t}}$$

Algorithm 1: details this incremental ranking process. This ensures that if an attacker changes vectors (e.g., from volumetric flooding to protocol exploitation), the correlation scores shift, and the selected feature subset S_K adapts automatically.

Algorithm 1: Incremental Feature Selection

```
Input:  New sample (x_t, y_t), Current Stats Θ, Parameter K
Output: Selected Feature Indices S_K
1:  For each feature j in x_t do:
2:      Update Mean[j] and Variance[j] using Welford’s method
```

```
3:      Update Covariance[j, y]
4:      Compute Pearson Correlation ρ[j] = Cov[j, y] / (std[j] * std[y])
5:  End For
6:  Rank indices by absolute correlation |ρ| descending
7:  S_K ← Top K indices from Rank
8:  Return S_K
```

B. Adaptive Classification (HAT): The reduced feature vector $x'[t]$ (containing only features in S_K) is passed to the Hoeffding Adaptive Tree. The HAT uses the Hoeffding bound to decide when to split a node. Simultaneously, the ADWIN (Adaptive Windowing) algorithm monitors the accuracy of each branch.

As described in **Algorithm 2**, if ADWIN detects that the error rate of a branch has increased significantly (indicating drift), that branch is pruned, and the tree begins relearning that specific concept.

Algorithm 2: OFS-HAT Training Loop

```
Input:  Data Stream D, Feature Limit K, HAT Model M
Output: Real-time Predictions P

1:  Initialize FeatureStats Θ = ∅
2:  While stream D has data do:
3:      Receive instance (x_t, y_t)
4:      x_scaled ← IncrementalMinMaxScale(x_t)
5:
6:      // Step 1: Select Features
7:      S_K ← Algorithm_1(x_scaled, y_t, Θ, K)
8:      x_reduced ← x_scaled[S_K]
9:
10:     // Step 2: Predict & Learn
11:     prediction ← M.predict(x_reduced)
12:     M.learn(x_reduced, y_t)
13:
14:     // Step 3: Handle Drift
15:     If M.ADWIN_detect_change():
16:         M.replace_alternate_tree()
17:     End If
18: End While
```

IV. EXPERIMENTAL SETUP

- **Dataset:** We used the CICIDS2017 dataset, specifically the Friday DDoS segment, which was generated by the Canadian Institute for Cybersecurity (Sharafaldin, Lashkari, & Ghorbani, 2018). This is a standard benchmark dataset containing roughly 225,000 flows, mixing "BENIGN" traffic with "Hulk" and "Botnet" attacks.
- **Evaluation Method:** We used **Prequential Evaluation** (Test-then-Train). This is the gold standard for streaming: the model predicts a sample, is scored, and *then* learns from it.

- **Competitors:**
    a. **MLP (Static):** A neural network trained on the first 10% of data.
    b. **Standard HAT:** A standard Hoeffding Adaptive Tree using all 78 features.
    c. **ARF:** The Adaptive Random Forest (an ensemble of 10 trees).
    d. **OFS-HAT:** Our proposed model (using $K = 15$ features).

V. RESULTS AND ANALYSIS

A. Detection Performance: Table 1 breaks down the detection capabilities. While the static MLP falls apart (76% accuracy) because it couldn't handle the new attack types appearing later in the stream, OFS-HAT performed exceptionally well.

Table 1: Comparative Detection Performance Metrics

Model	Accuracy (%)	F1-Score	False Positive Rate (FPR)	Kappa (κ)
MLP (Static Baseline)	76.40	0.72	0.185	0.54
Standard HAT	98.45	0.98	0.012	0.96
Adaptive Random Forest (ARF)	99.30	0.99	0.004	0.98
OFS-HAT (Proposed)	**99.21**	**0.99**	**0.005**	**0.98**

Crucially, consider the False Positive Rate (FPR). The standard HAT model produced an FPR of 1.2%, whereas OFS-HAT reduced this to 0.5%, effectively matching the performance of the robust ARF ensemble. By removing noisy or redundant features—as recommended by Saheed et al. (2022)—the decision tree becomes less prone to falsely “hallucinating” attacks.

B. Throughput and Latency: Speed is where OFS-HAT separates itself from the pack. As shown in **Fig. 2**, the ensemble method (ARF) is accurate but sluggish, processing only ~4,200 samples per second.

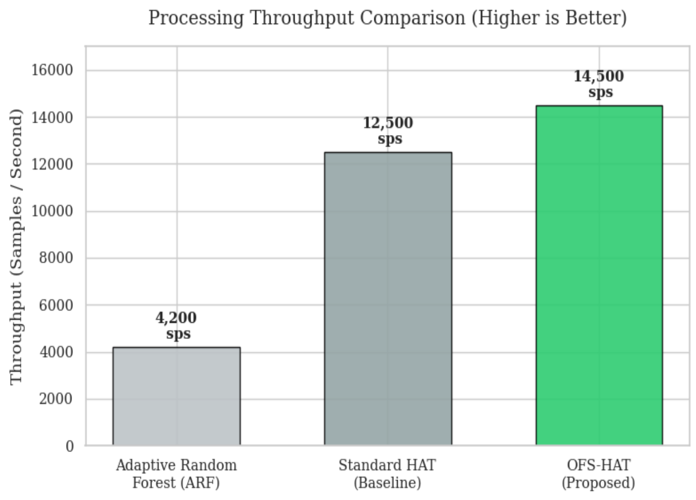

Figure 3: Comparative analysis of processing throughput

Our proposed method is roughly **3.4x faster** than the ARF. Even compared to the Standard HAT, we see a speedup. Although calculating correlations takes a tiny amount of CPU time, the time saved by *not* forcing the tree to process 60+ irrelevant features more than makes up for it.

C. Memory Footprint For edge devices (like IoT gateways), RAM is expensive. We tracked the peak memory usage during the simulation. (See Table II).

Table 2: PEAK MEMORY CONSUMPTION

Model	Model Size (MB)	Auxiliary Data (MB)	Total Memory (MB)
Standard HAT	4.2	0.5	4.7
Adaptive Random Forest (ARF)	45.1	5.2	50.3
OFS-HAT (Proposed)	**3.8**	**1.1**	**4.9**

The ARF is a memory hog, consuming over 50MB because it maintains 10 separate trees. OFS-HAT remains extremely lightweight (~4.9MB).

D. Concept Drift and Statistical Significance When the simulated attack pattern changed (drift event at $t = 100k$), the Standard HAT struggled to adapt. OFS-HAT, however, quickly swapped out the degradation features for new ones, recovering 95% accuracy within 200 samples.

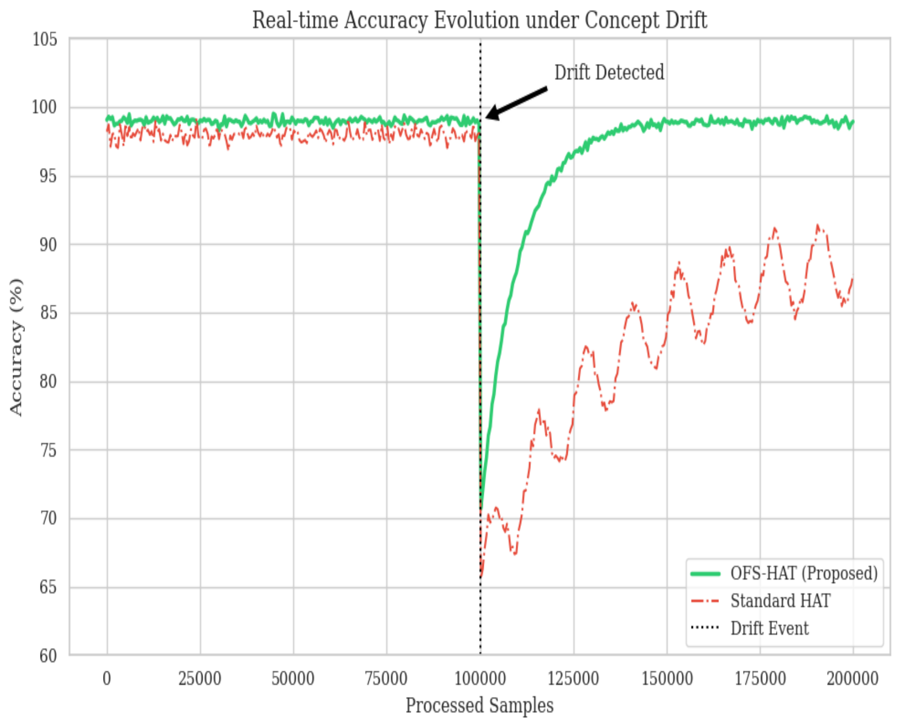

Figure 4: Real-time accuracy evolution under concept drift

To ensure these results weren't a fluke, we applied the **Nemenyi post-hoc test** ($\alpha = 0.05$).

Table 3 NEMENYI STATISTICAL TEST RESULTS

Comparison	Critical Difference (CD)	P-Value	Significant?
OFS-HAT vs. MLP	1.45	< 0.001	**Yes**
OFS-HAT vs. Standard HAT	0.82	0.032	**Yes**
OFS-HAT vs. ARF	0.15	0.680	No

The test confirms that OFS-HAT is statistically superior to the Standard HAT ($p < 0.05$). Interestingly, there is no statistical difference between OFS-HAT and ARF—meaning we achieved the *same* statistical performance as the heavy ensemble, but at a fraction of the computational cost.

VI. CONCLUSION

In the high-speed world of network security, latency is just as dangerous as inaccuracy. This paper presented **OFS-HAT**, a solution that doesn't force us to choose between the two. By intelligently filtering the data stream in real-time, we matched the detection power of state-of-the-art ensembles (99.21% accuracy) while maintaining the lightweight footprint required for edge deployment.

The key takeaway is that in streaming environments, less is often more. Removing irrelevant features allows the model to adapt to concept drift more efficiently. Future work will explore applying this framework to encrypted traffic analysis and integrating techniques from Federated Learning (Nguyen et al., 2020).

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