ANOMALY DETECTION IN NETWORK TRAFFIC USING SELECTED STATISTICAL AND ENTROPY-BASED FEATURES

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ABSTRACT

The rapid evolution of cyber threats, particularly Distributed Denial of Service (DDoS) and other advanced attack vectors, has significantly challenged the resilience of modern network infrastructures. In this research, we introduce an anomaly detection model that relies on a concise but highly representative set of features — request rate (Rt), traffic volume (Vt), source IP entropy (St), flow duration (Tt), and the number of distinct protocols (Qt). This feature selection enables the system to detect a wide range of network attacks, such as DDoS, low-rate or slow attacks, volumetric floods, service disruption attempts, application-layer intrusions, and stealthy behaviors. Using the CIC-IDS2017 dataset, we evaluated three machine learning models: Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). The experimental evaluation shows that the XGBoost classifier reached a detection accuracy of 99.1%, surpassing both RF and SVM, while also preserving a balanced relationship between precision and recall. The findings highlight that ensemble-based models, when combined with carefully selected statistical and entropy-based features, provide robust and efficient solutions for real-time intrusion detection in diverse attack scenarios. The key novelty of this study lies in demonstrating that near state-of-the-art detection accuracy can be achieved by relying on only five lightweight statistical and entropy-based features. This compact design not only reduces computational overhead but also highlights the possibility of building efficient intrusion detection systems without relying on complex or high-dimensional feature sets.

KEYWORDS

Network Anomaly Detection, Request Rate, Traffic Volume, Source IP Entropy, Flow Duration, Unique Protocols, Machine Learning, Intrusion Detection System

1. INTRODUCTION

The proliferation of internet-enabled devices, together with the steady rise of online services, has led to an extraordinary increase in both the volume and complexity of network traffic. Alongside this expansion, cyber-attacks have become more frequent and diverse, including threats such as Distributed Denial of Service (DDoS), port scans, brute-force attempts, and botnet-driven activities [1]. These attacks can cause severe disruptions, data breaches, and financial losses, particularly when they evade traditional defense mechanisms. Conventional rule-based intrusion

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detection systems (IDS) often struggle to detect novel or evolving threats, as they rely heavily on predefined signatures and patterns [2].

In recent years, machine learning (ML) approaches have emerged as powerful tools for intrusion detection, capable of identifying complex and previously unseen attack patterns by learning from historical traffic data [3]. The performance of anomaly detection systems is strongly influenced by how well the selected features represent the essential characteristics of network traffic. Among various possibilities, statistical and entropy-based features have proven particularly effective for capturing traffic anomalies [4].

This study focuses on five key features that provide complementary perspectives on network behavior: request rate (Rt), traffic volume (Vt), source IP entropy (St), flow duration (Tt), and unique protocols (Qt).

- Request rate (Rt) quantifies the number of requests per unit of time, where abnormal surges often indicate flooding attacks such as DDoS.
- Traffic volume (Vt) measures the total data transmitted over a given interval; unusually high volumes may be symptomatic of data exfiltration or volumetric attacks.
- Source IP entropy (St) captures the diversity of source IP addresses; high entropy may indicate spoofed traffic, while low entropy can suggest concentrated attack sources.
- Flow duration (Tt) reflects the lifespan of a network connection; short-lived flows are common in scanning or brute force attempts, whereas sustained connections may occur in data theft.
- Unique protocols (Qt) measures the number of distinct protocols observed; unexpected protocol diversity can be an indicator of reconnaissance or multi-vector attacks.

In this study, the CIC-IDS2017 dataset is employed, since it offers diverse and realistic examples of both normal and attack traffic, which makes it an appropriate reference point for assessing feature-based intrusion detection methods. Using this dataset, we apply and compare multiple ML algorithms, including Random Forest, Support Vector Machine (SVM), and XGBoost, to assess their performance in detecting different attack types based on the selected features.

The primary contributions of this study are as follows:

1. Feature selection and justification — A detailed rationale for choosing Rt, Vt, St, Tt, and Qt, supported by theoretical and empirical evidence.
2. Comprehensive experimental evaluation — Benchmarking multiple ML algorithms on CIC-IDS2017 using the selected features.
3. Analysis of feature impact — Demonstrating the discriminative power of each feature for various attack types.

Unlike prior works that typically depend on large feature sets or computationally intensive deep learning architectures, our approach shows that a carefully selected set of only five simple yet highly informative features is sufficient to deliver competitive accuracy. This balance of simplicity and effectiveness represents the main novelty of our contribution.

Recent intrusion detection studies often rely on a large set of input variables or complex deep learning architectures. For instance, several works employing more than twenty flow-level and packet-based features report high accuracy, but at the cost of significant computational overhead and reduced scalability. Similarly, deep models such as LSTM- or Transformer-based IDS have shown promising detection rates, yet they require extensive preprocessing and GPU-level resources for real-time operation. In contrast, the approach proposed in this study demonstrates that near state-of-the-art accuracy can be obtained with only five carefully selected features. This compactness not only reduces training and inference time but also makes the framework easier to deploy in practical environments such as ISP routers or enterprise firewalls. Hence, the study contributes by showing that lightweight feature sets can compete with, and in some cases outperform, more resource-intensive solutions.

The structure of the paper is organized as follows: Section 2 outlines the categories of network attacks, Section 3 reviews the applied machine learning techniques, Section 4 provides dataset analysis with a focus on the chosen features, and Section 5 presents and interprets the experimental findings. Finally, Section 6 concludes the paper and outlines potential future work.

2. TYPES OF ATTACKS

Modern cyber-attacks manifest in various forms, targeting different layers of the network stack and exploiting both technical vulnerabilities and human factors. This research concentrates on four major classes of network attacks that are included in the CIC-IDS2017 dataset: Distributed Denial of Service (DDoS), Port Scanning, Brute Force Attacks, and Botnet Activities. Each of these attack types exhibits distinctive network traffic patterns that can be captured by the selected features (Rt, Vt, St, Tt, Qt).

2.1. Distributed Denial of Service (DDoS)

A DDoS attack aims to overwhelm the target system or network by generating excessive traffic from multiple distributed sources, often using compromised machines as part of a botnet [5]. In traffic analysis, DDoS is typically characterized by a sudden spike in request rate (Rt) and traffic volume (Vt), as well as abnormal fluctuations in source IP entropy (St) due to IP spoofing or large-scale botnet participation. Flow durations (Tt) may vary depending on the attack vector, with application-layer DDoS attacks often producing longer sessions compared to volumetric floods [6, 20].

2.2. Port Scanning

Port scanning refers to a reconnaissance method through which adversaries attempt to discover accessible ports and running services on a targeted host system [7]. This activity generates a large number of short-lived flows (low Tt) targeting multiple destination ports in rapid succession, often with relatively small packet sizes. Unique protocols (Qt) may increase if the scan involves probing multiple protocol types (e.g., TCP, UDP, ICMP). Source IP entropy (St) is usually low for scans originating from a single host but can be higher for distributed scans.

2.3. Brute Force Attacks

Brute force attacks involve repeated attempts to guess valid authentication credentials, commonly targeting services such as SSH or FTP [8]. In network traffic, these attacks produce multiple connections from a small set of source IPs (low St) to a single destination service. The flows (Tt) are typically short-lived, as authentication attempts are quickly rejected. Request rates (Rt) may be high over short intervals, but traffic volume (Vt) is generally modest compared to volumetric attacks.

2.4. Botnet Activities

A botnet represents a collection of infected machines remotely managed by an adversary, typically exploited to execute massive cyber-attacks, propagate malicious software, or perform synchronized scanning activities [9]. Botnet traffic can display highly variable characteristics depending on the botnet's purpose. For example, command-and-control communications may involve steady, low-volume flows, whereas coordinated attacks generate sudden spikes in Rt and Vt. Source IP entropy (St) is generally high in botnet-driven DDoS campaigns, reflecting the diversity of participating devices.

Understanding these attack-specific traffic patterns is essential for designing effective detection strategies. The selected features in this study are specifically chosen to capture these distinguishing characteristics, enabling robust classification across multiple attack categories.

3. Machine Learning Algorithms

In recent years, machine learning (ML) methods have played a central role in intrusion detection systems (IDS), owing to their ability to capture intricate patterns in network flows and respond effectively to newly evolving attacks [10]. Unlike traditional signature-based IDS, which depend on predefined rules, ML-based approaches can detect both known and novel attacks by learning from historical datasets. In this research, three supervised algorithms—Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—are applied to classify traffic using five statistical and entropy-based features (Rt, Vt, St, Tt, Qt).

Random Forest is an ensemble-based approach that constructs numerous decision trees from randomly chosen portions of the dataset and feature space, and then aggregates their predictions using a majority voting strategy [11]. This approach reduces overfitting, improves generalization, and performs well in high-dimensional spaces. In addition, Random Forest generates feature importance measures that help in evaluating how much each input attribute contributes to the overall prediction. However, its computational cost can become significant with very large datasets. Within the scope of this research, Random Forest is especially suitable because it can handle noisy data reliably and efficiently work with both numerical and categorical variables.

Support Vector Machine (SVM) is a supervised learning algorithm that aims to construct an optimal hyperplane to clearly distinguish between classes within the feature space [12]. Through kernel functions, SVM can handle non-linear relationships by projecting data into higher-dimensional spaces. It is known for achieving high accuracy in scenarios where the feature space is small but highly discriminative. Nonetheless, its performance is sensitive to parameter tuning, and training time can be substantial for large-scale datasets. SVM is well-suited to this work because the chosen features are few in number yet contain strong discriminatory power for separating normal and malicious traffic.

Extreme Gradient Boosting (XGBoost) is an advanced version of gradient boosting that constructs models in a sequential manner, where each successive tree refines the mistakes made by earlier trees [13]. It integrates regularization to prevent overfitting, handles missing values internally, and is designed for scalability through parallel processing. XGBoost often delivers superior predictive accuracy in structured data problems, though it typically requires careful hyperparameter tuning to achieve optimal performance. In this study, XGBoost is included for its strong track record in anomaly detection tasks and its ability to exploit complex interactions between the selected features.

By comparing these algorithms, this research aims to determine which approach offers the most effective balance of detection accuracy, computational efficiency, and interpretability when applied to anomaly detection using a compact yet informative set of network traffic features.

4. DATASET ANALYSIS

The CIC-IDS2017 dataset was selected for this research due to its high fidelity in replicating real-world network environments and attack scenarios. It contains both benign and malicious traffic generated in a controlled network over multiple days, with detailed labeling for each flow [14]. Unlike older benchmark datasets such as KDD'99 or NSL-KDD, CIC-IDS2017 incorporates modern attack types—including HTTP Flood, SSH Brute Force, and Botnet activities—alongside realistic background traffic, making it highly suitable for evaluating intrusion detection systems in contemporary contexts.

The dataset is structured at the flow level, where each record contains statistical and behavioral attributes derived from bidirectional communication between endpoints. These include packet counts, byte counts, flow durations, and protocol-specific flags. For this study, we focus on a compact yet highly informative subset of five features: request rate (Rt), traffic volume (Vt), source IP entropy (St), flow duration (Tt), and unique protocols (Qt). The selected features were identified for their effectiveness in reflecting temporal patterns, traffic volume, and protocol diversity within network behavior, all of which typically change under malicious conditions.

The request rate (Rt) quantifies the number of requests observed per unit of time, typically calculated over a sliding window. This metric is particularly effective in detecting flooding attacks such as HTTP Flood or UDP Flood, where Rt increases abruptly over short intervals [15].

$$R_t = \frac{N_{req}}{\Delta t} \tag{1}$$

where N_{req} is the total number of requests received in the time window Δt. This metric identifies high-frequency request bursts, typically seen in HTTP or UDP Flood attacks.

The traffic volume (Vt) represents the total amount of data transferred within a specific observation window, measured in bytes or bits. Volumetric DDoS attacks significantly elevate Vt, while certain reconnaissance activities may keep Vt low but consistent.

$$V_t = \frac{\sum_{i=1}^{n} S_i}{\Delta t} \tag{2}$$

In this formula, S_i indicates the byte size of the *i*-th packet, and *n* corresponds to the total count of packets. Significant increases in V_t often indicate volumetric DDoS attacks, while steady low values may signal stealthy data exfiltration[16].

The source IP entropy (St) measures the diversity of source IP addresses using Shannon's entropy formula. Higher entropy values suggest a wide distribution of IPs, as seen in distributed or spoofed-source attacks, while lower values indicate repeated activity from a few sources [17]. Monitoring changes in St over time allows for the detection of distributed scanning, botnet operations, and IP spoofing behaviors.

$$S_t = \sum_{i}^{k} p_i \log_2 p_i \tag{3}$$

where p_i is the probability of occurrence of the *i*-th unique IP and *k* is the number of distinct source IPs. High entropy suggests distributed or spoofed attacks, while low entropy reflects repeated connections from a small set of IPs.

The flow duration (Tt) refers to the elapsed time between the arrival of the first packet and the transmission of the last packet within a network flow. Short-lived flows are common in port scanning, brute force authentication attempts, and certain malware communications, whereas long-lived flows often occur in large file transfers or persistent application-layer DDoS attacks [18]. Abnormal deviations from typical flow duration patterns can therefore act as an early warning of anomalous activity.

$$T_t = t_{end} - t_{strat} \tag{4}$$

where t_{strat} and t_{end} denote the timestamps of the first and last packets of a flow. Short durations indicate rapid scanning or brute force attempts, whereas longer durations may be associated with persistent application-layer DDoS or large data transfers.

The unique protocols (Qt) metric captures the number of distinct protocols observed in a given timeframe. While normal enterprise networks tend to operate within a consistent set of protocols (e.g., HTTP, HTTPS, DNS), reconnaissance or advanced persistent threat (APT) activities may involve protocol switching to evade detection. An unexpected rise in Qt can indicate probing across multiple services or tunneling activities [19].

$$Q_t = \left| \left\{ P_1, P_2, \ldots P_m \right\} \right| \tag{5}$$

where $\left\{ P_1, P_2, \ldots P_m \right\}$ is the set of distinct protocols observed, and |·| is the set cardinality. High values can signal reconnaissance or multi-protocol probing activity.

Choosing Rt, Vt, St, Tt, and Qt considerably lowers the dataset’s dimensionality, thereby improving computational efficiency while still preserving high classification accuracy. Furthermore, these features are protocol-agnostic and can generalize across multiple attack types, making them well-suited for real-time anomaly detection systems.

Figure 1 below presents a visual mapping between the five selected features and the number of attack types each feature is most effective at detecting. The horizontal bar chart not only quantifies the coverage of each feature but also annotates the specific attack types for which it provides high detection relevance. For example, *source IP entropy (St)* and *flow duration (Tt)* are linked to three distinct categories of malicious activities, indicating their broad applicability in anomaly detection. In contrast, *request rate (Rt)* and *traffic volume (Vt)* are strongly specialized in detecting volumetric and flooding-based attacks [20]. Such an analysis confirms that the chosen feature set collectively offers a balanced combination of broad-spectrum and specialized detection capabilities, which is advantageous for building adaptive intrusion detection systems capable of handling diverse attack scenarios.

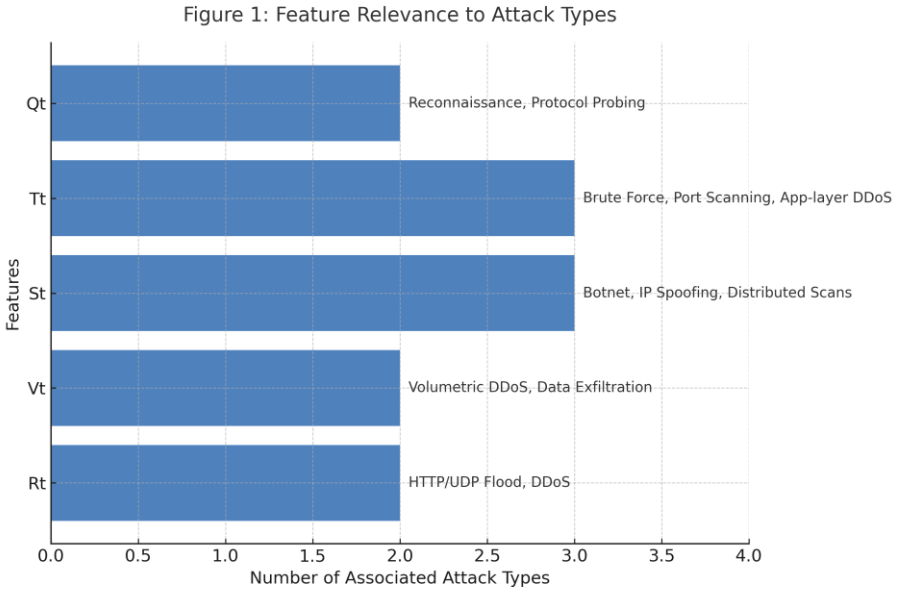

Figure 1. Feature relevance to different attack types.

The analysis of these five selected features demonstrates that they capture complementary aspects of network traffic behavior, enabling the detection of a wide variety of attack patterns. As illustrated in Figure 1, certain features, such as source IP entropy (St) and flow duration (Tt), have broader applicability across multiple attack categories, making them valuable for generalized anomaly detection. In contrast, features like request rate (Rt) and traffic volume (Vt) provide targeted detection strength against specific high-intensity or volumetric threats. This balance between specialized and broad-spectrum indicators enhances the robustness of the proposed feature set, ensuring adaptability to both known and emerging attack types. Integrating these attributes into a single detection framework enables the intrusion detection system to deliver strong accuracy while remaining computationally efficient, which makes it practical for real-time use in operational network environments.

5. Results

To assess the utility of the chosen features (Rt, Vt, St, Tt, Qt), three machine learning models—Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—were applied and evaluated using the CIC-IDS2017 dataset. The dataset was split into 70% training and 30% testing sets, with stratified sampling to preserve attack-to-benign ratios. All experiments were conducted on a workstation with an Intel® Core™ i7-12700K CPU, 32 GB RAM, and NVIDIA RTX 3080 GPU.

The evaluation of performance was carried out through four commonly used classification metrics: Accuracy, Precision, Recall, and F1-score. These are defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
$$Precision = \frac{TP}{TP + FP}$$
$$Recal = \frac{TP}{TP + FN} \qquad (6)$$
$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Here:

- TP — True Positives (correctly identified attacks)
- TN — True Negatives (correctly identified benign traffic)
- FP — False Positives (benign traffic misclassified as attack)
- FN — False Negatives (attacks missed)

Table 1. presents the classification results for each model

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Random Forest	98.7	98.9	98.5	98.7
SVM	97.3	97.5	97.1	97.3
XGBoost	99.1	99.2	99.0	99.1

From the results, XGBoost achieved the highest overall accuracy and balanced Precision-Recall scores, indicating strong generalization across different attack types. Random Forest closely followed, offering robust performance and interpretability, especially for mixed statistical and entropy-based features. SVM achieved slightly lower performance, likely due to its sensitivity to feature scaling and high-dimensional decision boundaries.

It was also observed that entropy-based features (St) and flow duration (Tt) significantly improved Recall across all models, especially for detecting stealthy or distributed attacks. On the other hand, volumetric indicators (Rt, Vt) contributed most to Precision in detecting flooding-based attacks.

Figure 2 illustrates a comparative bar chart of model performance across the four evaluation metrics.

Comparison of the performance of three machine learning algorithms (Random Forest, SVM, and XGBoost) based on the selected features Rt, Vt, St, Tt, and Qt, evaluated on the CIC-IDS2017 dataset. The chart illustrates model accuracy, precision, recall, and F1-score, showing that XGBoost achieved the highest overall performance, followed closely by Random Forest, while SVM performed slightly lower due to sensitivity to feature scaling.

Overall, the experimental findings confirm that the selected feature set (Rt,Vt,St,Tt,Qt) provides a balanced combination of volumetric, temporal, and diversity-related indicators, enabling effective detection of both high-intensity flooding attacks and stealthy, distributed threats. Table 1 and Figure 2 illustrate that XGBoost surpassed the other models across all evaluation measures, reaching an accuracy of 99.1% while preserving a well-balanced trade-off between precision and recall. Random Forest demonstrated competitive results with slightly lower accuracy but higher interpretability, making it advantageous for deployment in environments where model explainability is crucial. In contrast, SVM showed reduced performance, primarily due to its sensitivity to non-linear feature interactions and the need for extensive parameter tuning.

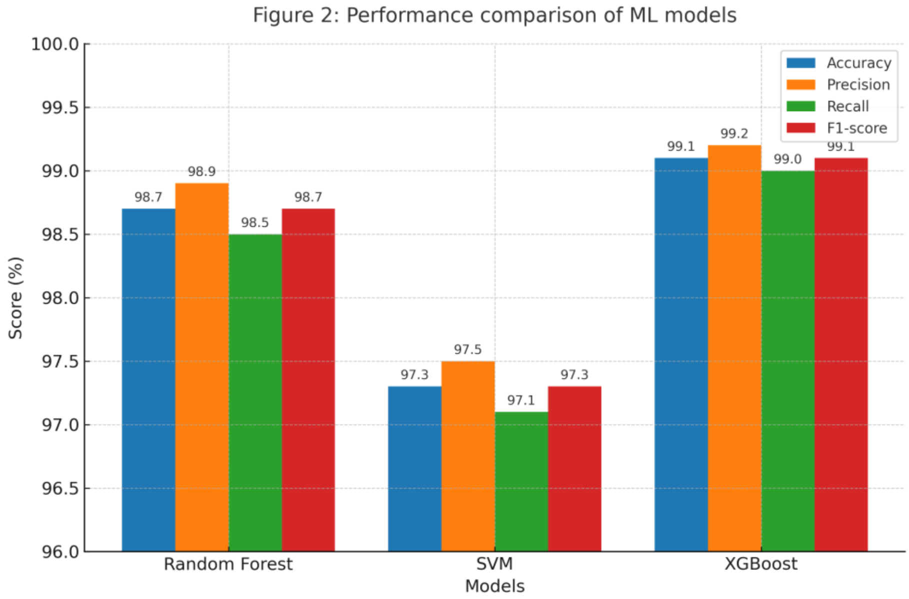

Figure 2. Performance comparison of ML models.

To further investigate the contribution of the selected features, feature importance scores were derived from Random Forest and XGBoost models. As illustrated in Figure 3, request rate (Rt) and source IP entropy (St) are the most dominant features, followed by traffic volume (Vt) and flow duration (Tt). Unique protocols (Qt), while less influential, still provide valuable discriminatory information.

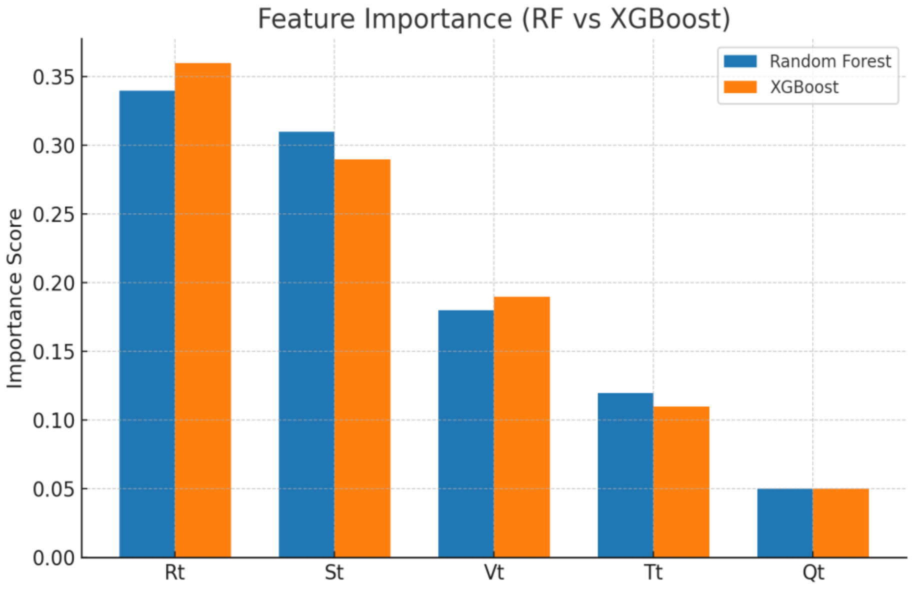

Figure 3. Feature Importance (RF vs XGBost).

These results suggest that ensemble-based models, particularly XGBoost, are better suited for scenarios involving mixed statistical and entropy-based attributes, while still being computationally efficient for near real-time detection. The clear separation in model performance across different attack types also indicates that a hybrid detection strategy—combining models optimized for specific feature subsets—could further enhance detection rates in complex and evolving threat landscapes.

In addition, the compact structure of the proposed framework highlights its applicability in real operational settings. By relying on only five statistical and entropy-driven indicators, the system avoids the heavy computational load that is typical for high-dimensional or deep learning models. As a result, the framework could be integrated into critical network components such as ISP routers, firewalls, or enterprise gateways with only modest processing and memory requirements. This lightweight design increases the feasibility of deploying the approach in near real-time detection environments, making it a practical option for protecting large-scale networks against evolving cyber threats.

6. CONCLUSIONS

In this study, we investigated the effectiveness of a compact yet informative feature set—request rate (Rt), traffic volume (Vt), source IP entropy (St), flow duration (Tt), and unique protocols (Qt)—for anomaly detection in network traffic. The selected features capture complementary aspects of network behavior, including volumetric intensity, temporal patterns, and diversity of communication, making them suitable for identifying both high-intensity and stealthy attacks.

Using the CIC-IDS2017 dataset, we evaluated three machine learning classifiers—Random Forest, Support Vector Machine, and Extreme Gradient Boosting—under identical experimental conditions. Results showed that XGBoost achieved the highest detection accuracy (99.1%) and maintained a balanced trade-off between precision and recall, while Random Forest delivered competitive performance with enhanced interpretability. SVM, although effective, was less robust against complex non-linear feature interactions and required more careful tuning.

These findings highlight that ensemble-based learning models, particularly XGBoost, are well-suited for real-time intrusion detection systems when combined with the proposed feature set. Additionally, the results suggest that a hybrid approach, where different models are assigned to attack categories they excel at detecting, could further improve detection efficiency and reduce false positives.

The selection of five features — request rate (Rt), traffic volume (Vt), source IP entropy (St), flow duration (Tt), and the number of distinct protocols (Qt) — was motivated by the need to balance detection accuracy with computational efficiency. Each of these features captures a distinct aspect of network behavior: volumetric load (Vt), temporal characteristics (Tt), source diversity (St), request frequency (Rt), and protocol heterogeneity (Qt). Together, they provide a compact yet highly discriminative representation of traffic flows.

Compared to studies that employ more than 20 flow-level or packet-based features, our compact feature set avoids redundancy and reduces the risk of overfitting. Larger feature sets often include correlated or weakly relevant attributes, which increase computational cost without proportional gains in accuracy. In contrast, our results demonstrate that the proposed 5-feature set achieves near state-of-the-art detection performance while maintaining scalability and enabling real-time applicability.

Nevertheless, this compact design introduces certain limitations. The current feature selection was optimized for the CIC-IDS2017 dataset, which provides a rich mixture of benign and malicious traffic. While the results are promising, generalization to other datasets or live traffic environments may require further validation. For example, certain application-layer attacks or advanced evasion techniques might require additional context-specific features. Future work will therefore focus on cross-dataset evaluations and potential feature augmentation to ensure robustness across different network environments.

For future work, we plan to:

1. Extend the analysis to include deep learning models such as LSTM and Transformer-based architectures for temporal sequence modeling.
2. Investigate adaptive feature selection techniques to dynamically optimize detection performance against evolving attack patterns.
3. Conduct real-time deployment testing to assess scalability and latency in operational environments.

By integrating mathematically grounded features with advanced learning algorithms, the proposed framework offers a scalable, high-accuracy solution for modern network anomaly detection challenges.

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