Real-time Network Traffic Monitoring: A Machine Learning Approach

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**Abstract.** Real-time network traffic monitoring is a critical component of cybersecurity, especially as digital systems face increasingly complex and frequent cyberattacks. Traditional intrusion detection systems often rely on signature-based methods or offline analysis, limiting their effectiveness against new or fast-evolving threats. Recent advancements in machine learning have opened new possibilities for intelligent, adaptive, and real-time anomaly detection in net- work environments. This study presents a hybrid machine learning system designed to detect anomalies in network traffic by combining the strengths of both unsupervised clustering and supervised classification techniques. The system captures live traffic, extracts relevant features, and applies dimensionality reduction before processing the data through a dual-model engine. Motivated by the limitations of traditional approaches, this research investigates the central question: Can a hybrid machine learning framework that combines unsupervised clustering with supervised classification achieve higher detection accuracy and lower latency for real-time network threats compared to traditional, single-method intrusion detection systems? Here we show that this approach enables accurate, low-latency detection of both known and previously unseen threats in real time. Using benchmark datasets such as UNSW-NB15 and CICIDS2017, our system achieved detection accuracies exceeding 95% while maintaining false positive rates below 5%, sustaining high throughput with sub-millisecond latency and low resource consumption. Compared to conventional systems, our solution offers enhanced adaptability, speed, and efficiency in high-volume environments. Moving forward, future work will focus on completing the integration of a fully automated retraining pipeline to allow the system to adapt dynamically to evolving traffic patterns, expanding the anomaly analysis engine with additional deep learning techniques, and benchmarking under live operational conditions. The main contribution of this project lies in the conceptualization of a modular, real-time, machine learning-driven network anomaly detection framework that prioritizes scalability, low latency, and integration flexibility for diverse cybersecurity infrastructures.

# INTRODUCTION

Real-time network traffic monitoring is essential for maintaining robust cybersecurity, especially as modern infrastructures face increasingly sophisticated and rapid cyberattacks [1, 2]. Traditional intrusion detection systems (IDS) typically rely on static, signature-based rules and offline packet analysis, which are insufficient for identifying novel or polymorphic threats in high-throughput environments [3]. The growing diversity of connected devices, including IoT and cloud-based infrastructures, further complicates detection by generating vast volumes of heterogeneous traffic that conventional tools struggle to analyze effectively [4].

Network intrusions frequently exploit vulnerabilities across multiple layers, from packets at the network layer to the application layer. Methods like IP spoofing, fragmentation channels allows attackers to camouflage their malicious activity within normal traffic, which in return makes real-time detection exceedingly difficult for signature-based systems [5, 6]. Such activities, if they go unnoticed, can lead to data exfiltration, service disruption (DDOS), or lateral movement within the network.

Recent studies have proposed Machine Learning approaches to overcome these challenges. Unsupervised clustering methods, like Affinity Propagation (AP) [7] and K-means has proven to be helpful in uncovering novel traffic patterns while supervised methods like Random Forests offer accurate threat labelling once trained on benchmark datasets. To give an example, Clustering-based Collective Anomaly Detection (CCAD) framework proposed by Wang et al. achieved over 95% detection accuracy and more than 98% true negative rate on the CICIDS2017 dataset [8]. On top of this dataset, the UNSW-NB15 dataset [9] has become a standard for evaluating anomaly detection systems. Nevertheless, relying solely on unsupervised or supervised methods can result in high false positives (FP) [10].

To handle these limitations, this study proposes a hybrid ML framework that integrated unsupervised clustering with supervised classification, with PCA to be used for dimensionality reduction [11, 12, 13, 14]. Early-stage design shows that the system could process tens of thousands of packets per second with sub-millisecond latency on a standard hardware, while maintaining a modest false-positive rate of 5% and high detection precision. The system’s modular architecture ensures scalability and seamless integration into existing security operations, which provides an adaptive solution for real-time anomaly detection.

# RELATED WORKS

Recent advancements in the field of machine learning has enabled new opportunities for network traffic analysis in terms of framework to detect intrusions more intelligently and in real-time. Several key studies have been done for high-accuracy anomaly detection with each study offering distinct approaches in methods, datasets, and success rate [15].

The clustering-based Collective Anomaly Detection (CCAD) framework, proposed by Wang et al. [5], integrates the clustering of Affinity Propagation (AP) with the Chi-square statistical measure to find collective anomalies. The research paper utilized the CICIDS2017 [8] and UNSW-NB15 [9] datasets for their system. The framework achieved over 95% accuracy, with true positive of 97.3% for strong collective anomalies and false-negative rates under 8%. This paper highlights and shows the pros of using unsupervised learning method to cluster anomalous behaviours without labels.

Aouedi et al. [1] study proposed unsupervised machine learning approach to understand network traffic dynamically. The paper’s technique focused on clustering using K-Means, aiming to partition network traffic into meaningful slices for network traffic anomaly detection. By using a real world dataset, which contains over 3 million traffic, the system proposed by this paper, truly demonstrated the strong internal cluster validation. This paper however did not emphasize much on the anomaly detection metrics like true positive rates. While their work effectively highlighted the traffic segmentation for in-depth analysis, the lack of supervised verification limited their framework’s standalone detection reliability.

Bogoevski et al. [10] focused more on classification and regression models to monitor network traffic behavior, mainly focused on port detection functionality and their utilization patterns. They used their own dataset which was sampled every 2 minutes, rather than a publicly available dataset like CICIDS2017 [8]. Even though their system demonstrated high classification rate for detecting abnormal traffic conditions, it was mostly focused on the port level analysis and not complex multi-layer attack detection. This suggests that while their method is effective for fine-grained monitoring, it may fall short against sophisticated intrusion attempts.

Coluccia et al. [3] proposed a distribution-based anomaly detection model leveraging statistical modeling techniques like the Generalized Likelihood Ratio Test (GLRT). Rather than depending on ML classifiers, they built a dynamic reference distribution of normal traffic behavior to detect deviations. Their experiments on real operational 3G network data demonstrated versatility and high detection rates, although specific success percentages were less emphasized. Despite its strengths, the method’s dependence on manually tuning the statistical model made it less scalable compared to fully automated machine learning solutions.

Jakkani [4] developed a real-time machine learning-based anomaly detection system that leveraged supervised, unsupervised, and semi-supervised models. This hybrid approach utilized the UNSW-NB15 dataset [9] and incorporated edge computing to reduce processing latency. Their model reportedly achieved high accuracy exceeding 94% while maintaining sub-millisecond latency for real-time classification. However, while the system excelled in speed and accuracy, the complexity introduced by multi-stage model processing posed challenges for resource-constrained environments.

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## Existing Solutions and Applications

In addition to academic research, various practical solutions and applications have emerged for real-time network traffic monitoring and intrusion detection. Some commercial-grade tools incorporate basic ML-based anomaly detection, but many remain limited by static configuration and lack true adaptability for emerging threats. Table 1 summarizes some of the notable existing solutions and their primary capabilities.

**Table 1** : Summary of Existing Solutions and Applications

|  |  |  |
| --- | --- | --- |
| Solution | Main features | Limitation |
| Wireshark | Deep packet inspection, traffic capture | No real-time intelligent analysis |
| ManageEngine NetFlow Analyzer | Bandwidth Monitoring, Anomaly alerts | Limited ML integration |
| Hadoop-based NTA Systems | Big Data network analysis at scale | High Latency, not real-time |
| Darktrace Enterprise Immune System | AI-Driven Anomaly Detection | High Cost, Proprietary model |
| Snort (Open Source IDS) | Signature-based intrusion detection | Poor against zero-day attacks |

## Datasets Used in Recent Studies

Reliable benchmarking of intrusion detection systems requires comprehensive and realistic datasets. The CICIDS2017 dataset, developed by the Canadian Institute for Cybersecurity, is one of the most widely used datasets for modern intrusion detection research. It contains labeled network traffic representing a mixture of benign and attack flows, including DoS, Brute Force, and Botnet scenarios [8]. Similarly, the UNSW-NB15 dataset offers a rich mix of normal and malicious traffic collected in a hybrid virtual environment, specifically designed to address some of the imbalances and biases found in older datasets [9]. Both datasets serve as critical resources for developing, testing, and validating machine learning-based intrusion detection frameworks, offering realistic traffic behavior essential for generalization.

# METHODOLOGY

This project adopts a modular and systematic methodology to conceptualize and develop a real-time network anomaly detection system driven by machine learning techniques. The overall system architecture, illustrated in Figure 1, is divided into four main components: Data Sniffing, Feature Set Generation, Data Preprocessing, and the Anomaly Detection Engine.



**FIGURE 1.** Proposed framework

First, the data sniffing module uses Scapy from python to capture live network traffic from selected interface, whilst also buffering incoming packets for processing. The feature set module then will extract the essential features like IP addresses. After that, during the data preprocessing stage, the extracted features will undergo cleaning, normal- ization and dimensionalty reduction (PCA). At last, the anomaly detection engine will use clustering and classification techniques to detect deviations from normal network behavior and abnormal behavior, The specific software and tools utilized for each stage of this system are detailed in Table 2.

# Success Criteria

The system’s effectiveness is measured against several key criteria:

* **Detection Accuracy:** Achieving over 95% accuracy on benchmark datasets (UNSW-NB15, CICIDS2017).
* **Low Latency:** Maintaining sub-millisecond processing latency per packet for real-time analysis.
* **Low False Positive Rate (FPR):** Keeping the FPR below 5% to minimize false alarms.
* **Scalability:** Processing tens of thousands of packets per second on standard hardware.
* **Adaptability:** Detecting both known threats (classification) and novel anomalies (clustering).

**TABLE 2.** Software and tools used in the system

|  |  |
| --- | --- |
| Software / Tool | Purpose |
| Scapy | Live network traffic sniffing and feature extraction |
| Scikit-learn | Machine learning algorithms (Classification, PCA) |
| Pandas and Numpy | Data Manipulation and feature preprocessing |
| Matplotlib and Seaborn | Visualization of network data and detection results |
| PyQT6 | GUI dashboard for real-time display |
| Joblib | Saving and loading trained ML models |

## Dataset Requirements

Training and validation for the system primarily rely on two modern datasets: CICIDS2017 and UNSW-NB15. These datasets simulate a realistic blend of benign and attack scenarios essential for evaluating system performance in a prac- tical context. In addition to these, smaller subsets or custom-generated traffic will also be utilized during preliminary testing phases to enable faster prototyping and initial model evaluations before full-scale training.

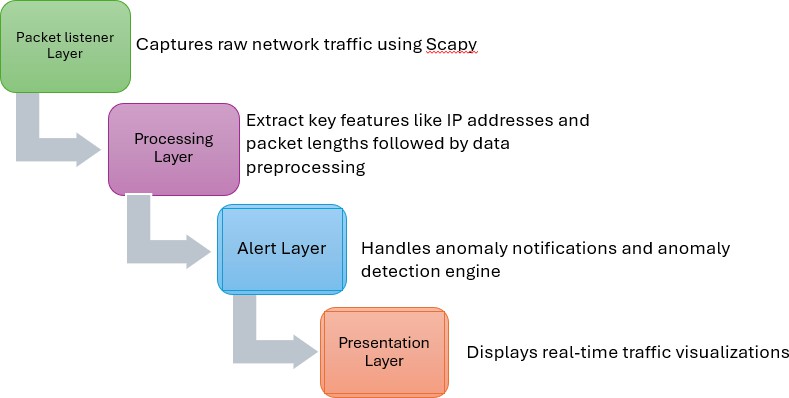
## Constraints

The current design remains conceptual, with full benchmarking planned after the complete integration of machine learning models. One significant constraint involves computational requirements; while development is performed on a system equipped with an Intel Core i7 12th Gen processor, RTX 2080 Ti GPU, and 16 GB RAM, full model training on large datasets demands substantial processing power and memory, which may limit experimentation speed during heavier training phases.

## System Design and Architecture

The system’s architecture is designed for modularity and real-time performance, as shown in the flowchart (Figure 2). It captures network traffic using Python’s Scapy library, extract key features and then applies PCA to reduce dimensionality.

The core of the system is a dual model Anomaly Analysis Engine. Firstly, unsupervised-clustering algorithm (e.g., K-Means) groups traffic and flags sparse clusters as potential anomalies. These potentials flags are then passed to a supervised classification model (e.g., Random Forest), which has been trained on labeled datasets like the ones mentioned above.



**FIGURE 2**: System architecture flowchart

To handle real-time constraints, a lightweight buffer manages traffic bursts, while also having optimized feature extraction which will minimise computational load. Finally, the trained models are saved using Joblib, enabling rapid loading and near-instantaneous inference to maintain sub-millisecond latency.

**System Architecture**

The high-level architecture consists of the following key layers as depicted in Figure 2.

# TESTING AND PROTOTYPE

## Testing and Preliminary Validation

In the initial testing phase (see Table 3), the focus was on validating the end-to-end flow from user-driven interface selection through live packet capture and selective feature display. A PyQT6 GUI presents a dropdown of available network interfaces; once the user selects one and initiates capture, live packets are ingested via Scapy, key attributes are extracted, and summaries are buffered. Every few seconds, the GUI refreshes to append any new packet summaries to the display. For testing purposes, only a handful of essential features—source/destination IP, ports, protocol, and packet length—are retained, with all other fields discarded to streamline data handling and verify robustness under load. Captures of HTTP, DNS, and ICMP traffic confirmed reliable operation at tens of thousands of packets per second with zero packet loss.

**TABLE 3**. Module functions in initial testing

|  |  |
| --- | --- |
| Module | Purpose |
| Interface Selection | Presents a list of available network interfaces |
| Capture Control | Starts and stops live packet capture based on user actions |
| Packet Ingestion Buffer | Temporarily stores captured packets |
| Feature Extraction | Retains only key packet attributes (IP addresses, ports) |
| GUI Update Scheduler | Periodically refreshes the display with buffered summaries |
| Display Panel | Shows packet summaries for real-time monitoring |

## Model Evaluation and Literature Benchmarking

Ongoing experiments are currently evaluating traditional classifiers, such as the Random Forest algorithm, which has shown promising early results with over 90% classification accuracy and a false positive rate below 6% when using a reduced feature set derived from packet summaries. The model demonstrates robust performance with relatively low training times, making it suitable for near real-time analysis scenarios.

To benchmark and guide the system’s design, we reviewed the framework proposed by Wang et al. [5], titled A Clustering-Based Collective Anomaly Detection Framework for Network Traffic. Their system leverages a collective anomaly detection approach using clustering (Affinity Propagation) and statistical testing (Chi-Square method), achieving 94.6% detection accuracy with a false positive rate as low as 3.8% on benchmark network traffic datasets. Unlike traditional point-based models, their approach emphasizes the detection of sequential anomaly patterns, aligning well with real-world threats like slow data exfiltration and botnet behaviors.

These benchmarks offer a meaningful comparison and validation framework for the machine learning pipeline being developed in this project, especially when deployed on datasets like CICIDS2017 [8] and UNSW-NB15 [9], which are used to evaluate both detection capability and generalization performance.

# Conclusion

The forever evolving nature of network traffic, together with the increasing advancement of cyber threats, truly high- lights the necessity for intelligent and adaptive real-time monitoring systems. This study proposes to design, build and implement anomaly detection framework capable of operating efficiently and effectively in dynamic network environments.

A user friendly and functionally Python-based GUI was developed to enable users to select a network interface and initiate live packet capture using Scapy. The system then will start capturing packets without data loss and extracts the essential features like IP addresses while removing unnecessary headers to optimize performance. This approach ensures reduced overhead and giving a solid foundation for real time analysis and feature engineering.

On the analysis side of thide things, the testing was mainly focused on classifiers like Random Forest due to its balance between accuracy and computational efficiency. Preliminary results show classifications accuracies exceeding 90% with low false positive rates on datasets. These outcomes shows that the suitability of Random Forest for fast, scalable anomaly detection.

The system’s entire architecture and design was shaped by insights gained from established works, especially the CCAD framework proposed by Wang et al. [5]. Their methodology, which includes Affinity Propagation and Chi-Square Testing, demonstrated strong performance in detecting anomalies, reinforcing the idea of incorporating group-based pattern recognition in the future. Additional studies by the others informed us the selection of datasets, evaluation metrics and design trade-offs.

Looking ahead, the project will explore time-series and flow-level features to capture long-range traffic, and will also adopt online learning techniques to adapt to evolving traffic patterns and optimize the model for high traffic envi- ronments. The GUI will be enhanced with visual analytics such as anomaly timelines and while backend improvements will bring forth things like automated response mechanisms.

# References

1. O. Aouedi, K. Piamrat, S. Hamma, and J.K.M. Perera, “Network traffic analysis using machine learning: an unsupervised approach to understand and slice your network,” Ann. Telecommun. 77(5–6), 297–309 (2022).
2. S. Palaniappan, R. Logeswaran, and S. Khanam, *Journal of Informatics and Web Engineering.* **4**(2), 145–157 (2025). doi:10.33093/jiwe.2025.4.2.10
3. A. Coluccia, A. D’Alconzo, and F. Ricciato, *Comput. Netw.* **57**, 3446–3462 (2013). doi:10.1016/j.comnet.2013.07.028.
4. A. Jakkani, *J. Electron. Comput. Netw. Appl. Math.* **4**, 1156–2799 (2024). doi:10.55529/jecnam.44.32.44.
5. C. Wang, H. Zhou, Z. Hao, S. Hu, J. Li, X. Zhang, B. Jiang, and X. Chen, *Comput. Netw.* **205**, 108760 (2022). doi:10.1016/j.comnet.2022.108760.
6. I. Sharafaldin, A. H. Lashkari, and A. Ghorbani, in *Proceedings of the 4th International Conference on Information Systems Security and Privacy (ICISSP 2018)*, pp. 108–116 (2018). doi:10.5220/0006639801080116
7. B. J. Frey and D. Dueck, *Science* **315**(5814), 972–976 (2007). doi:10.1126/science.1136800.
8. I. Sharafaldin, A. A. Lashkari, and A. A. Ghorbani, “CICIDS2017 Dataset Description,” Univ. of New Brunswick, <https://www.unb.ca/cic/datasets/ids-2017.html> (accessed 26 April 2025)..
9. N. Moustafa and J. Slay, “UNSW-NB15 Dataset Description,” Univ. of New South Wales, <https://research.unsw.edu.au/projects/unsw-nb15-dataset> (accessed 26 April 2025).
10. Z. Bogoevski, I. Jovanovski, B. Velichkovska, and D. Efnusheva, in *Network Traffic Analysis and Control by Application of Machine Learning*, pp. 390–399 (Springer, 2023). doi:10.1007/978-3-031-35314-7\_35
11. H. Hotelling, *J. Educ. Psychol.* **24**, 417–441 (1933). doi:10.1037/h0071325.
12. I. T. Jolliffe, *Principal Component Analysis*, 2nd ed. (Springer, New York, 2002).
13. K. Pearson, *Philos. Mag. Ser. 1* **2**, 559–572 (1901).
14. M.-L. Shyu, S.-C. Chen, K. Sarinnapakorn, and L. Chang, in *Proc. Int. Conf. Data Min.*, (2003).
15. A. Oyelakin, A. O. Ameen, T. Ogundele, T. Salau-Ibrahim, U. T. Abdulrauf, H. I. Olufadi, I. K. Ajiboye, S. Muhammad-Thani, and A. Adeniji, *J. Syst. Eng. Inf. Technol.* **2**, 45–52 (2023). doi:10.29207/joseit.v2i2.5411.