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Targeted Detection of Advanced Persistent Threats in Cloud-Native Environments: A Focused Machine Learning Approach

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Targeted Detection of Advanced Persistent Threats in Cloud-Native Environments: A Focused Machine Learning Approach

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Abstract

This research presents a machine learning-based framework for detecting Advanced Persistent Threats (APTs) within containerized cloud-native environments systems increasingly targeted in attacks like the SolarWinds breach and Kubernetes API server exploits. Unlike traditional intrusion detection systems that struggle with dynamic cloud features such as ephemeral containers and inter-service communication, our approach leverages real-time Zeek telemetry and Falco runtime alerts to capture both network and behavioral anomalies. Through synthetic attack simulations aligned with real-world CVEs and CWEs, we curated three threat datasets PT_TRAIN, OSCI, and UUF and benchmarked them alongside live Zeek logs. Feature engineering was applied on parsed conn.log data, and supervised (Random Forest) and unsupervised (Isolation Forest) models were trained. Random Forest achieved F1-scores between (0.94 to 1.00) on curated datasets, but performance collapsed to F1=0.10 on live Zeek data underscoring the need for labelled data in cloud threat detection. This work differs from prior studies by integrating both telemetry and runtime signals in a reproducible pipeline tailored for microservice-based systems. Our results demonstrate that data quality not algorithm choice is decisive factor and this is a scalable and practical approach to modern APT detection that bridges the gap between synthetic data modelling and real-world applicability.

1 Introduction

1.1 Background

The rise of cloud-native technologies, including containerization (e.g. Docker) and orchestration frameworks like Kubernetes, has led to a dramatic transformation in enterprise IT infrastructure. By 2024, over 85% of global enterprises were using containerized applications in production (Gartner, 2023), and Kubernetes became the de facto standard for managing those workloads. These environments offer substantial advantages in scalability, agility, and modular design through microservices. However, the same characteristics ephemerality, auto-scaling, and dynamic service discovery introduce a significant attack surface for threat actors.

Cloud-native workloads are ephemeral; for instance, a container may only run for seconds or minutes, and some may even require high levels of distribution by communicating through internal APIs which traditional perimeter security solutions are not able to monitor effectively (Lindvall et al., 2021). In doing so, attackers need to exploit these blind spots and

more exploited these blind spots incorporate quiet, long-haul intrusions called Advanced Persistent Threats (APTs).
A prime example of such an APT is the infamous SolarWinds breach, a supply chain attack that was able to breach thousands of governments and corporate systems in 2020, where the attacker was able to remain hidden for months by infiltrating the CI/CD pipeline. Likewise, Kubernetes-specific exploits like CVE-2020-8554 and CVE-2021-25741 were exploited to access unauthorized on account of API server misconfiguration and privilege escalation in multi-tenant clusters (CISA, 2022).
Static rules or signature-matching-based traditional intrusion detection systems (IDS) fail to scale when applied to the complex telemetry of containerized workloads. They were never intended to log things like live inter-service traffic, ephemeral container logs, nor any of the runtime actions inside of namespaces and pods. Even more critically, they often miss threats that are cloud-specific and outside of classical threat models.

To overcome these limitations, there has been a recent trend in both research and enterprise toward using machine learning for threat detection because machine learning can learn from the entire high volume and high dimensionality of network data and plus also practice for system data. Parameters such as Random Forest and Isolation Forest machine learning (ML) algorithms (Ghosh et al., 2023) do this dynamically by modelling normal behavior and providing cost-effective and suitable detection of anomalies that deviate from expected patterns, which makes them better ideations to detect APTs in microservice-based architectures.

We use an open-source network security monitor Zeek and a Cloud Native Computing Foundation (CNCF) adopted runtime security tool Falco to produce and analyses telemetry data for real or simulated attack surfaces. Using APT datasets PT_TRAIN, UUF, and OSCI we build a machine-learning pipeline able to detect in real-time known and unknown APT behavior. Thus, Cloud-Plain provides a modern, context-aware, and scalable answer to a key cybersecurity problem for cloud-native environments.

1.2 Problem Statement

Traditional intrusion detection systems are ineffective against stealthy and low and slow Advanced Persistent Threats in dynamic cloud-native environments due to high false positive rates, lack of context-aware feature engineering, and limited availability of labelled data for training robust machine learning models.

1.3 Research Motivation

This part of the bigger picture, as one of the main motivations of this work is to bridge the main gap between the cloud-native infrastructure monitoring and APT detection. Modern IDS platforms are incorporated yet, they often fail to meet the specific needs of containerized environment, due to containers being time-sensitive, dynamically changing network environment and evolving threat scenarios approached using gradual, stealthy techniques. However, there is no easy-to-adopt, validated framework that combines open, real-time (e.g., Zeek, Suricata) with curated APT datasets suitable for ML-based evaluation and training.

Few studies compare supervised and unsupervised models directly by using the same cloud-native attack scenarios, offering practitioners limited guidance on how to choose the right model for real-world deployment. In addition to providing this comparison, the study also presents reproducible methods and relatively interpretable results that can be integrate into modern DevSecOps pipelines.

1.4 Research Objective

The objective of this research is to develop a robust and adaptable machine learning framework for detecting advanced persistent threats (APTs) within containerized cloud- native environments. This study seeks to bridge the gap between traditional intrusion detection approaches and the evolving landscape of cloud-native security by leveraging real- time network and behavioral analysis. The proposed framework aims to detect both known and unknown threats by combining data-driven anomaly detection with pattern-based learning, thereby enabling proactive threat mitigation. By evaluating multiple detection strategies across varied threat scenarios, this research aims to provide comprehensive insights into the applicability and effectiveness of machine learning methods in enhancing threat visibility and resilience in cloud-native infrastructures.

1.5 Research Questions

- **How can machine learning techniques be effectively utilized to detect and classify advanced persistent threats (APTs) in containerized cloud-native environments using network data?**
- **What are the comparative strengths and limitations of supervised and unsupervised machine learning models in identifying malicious traffic patterns across diverse threat conditions and datasets?**

1.6 Research Gap

Most of existing research is focused on intrusion detection using machine learning (ML) in traditional network architectures or at static cloud configurations, with limited attention given unique characteristics containerized cloud-native environments (Sharma et al., 2023; Zhang and Lee, 2022). Ephemeral containers and dynamic interactions with microservices necessary security models that can adapt to changes. Currently, APT detection methods depend on static rule-based techniques or dated datasets, which do not account for changing attack vectors or variable traffic patterns (Khan et al., 2021).

Moreover, a number of models that were proposed in past research have not been practically realized as they do not integrate with real-time tools (Gao et al., 2022, 2022). Only a few studies have compared the supervised and unsupervised models over diverse, labelled APT datasets that adhere to real-world CVEs and CWEs. Many labelling methods lack transparency and/or realism when labelling is simulated by synthetic attack simulation.

To address this limitation, our research proposes an accessible and reproducible ML-based framework designed for cloud-native environment. This framework uses Zeek(tool),

simulated and well-crafted APT datasets and a comparative model evaluation aimed at cloud-native environments.

2 Related Work

2.1 Kubernetes Related Works

The increase in Advanced Persistent Threats (APTs) in cloud-native infrastructure has changed the focus of security research, especially in terms of machine learning (ML) and deep learning (DL). Abstract The dynamic and ephemeral nature of containers such as Kubernetes present challenges in detection gaps for traditional intrusion detection systems (IDS), which are often not designed to effectively operate in evolving application environments. In this section, we perform a critical review of recently published works on APT detection, highlighting ML-based techniques particularly focused on containerized and microservice-based APT environments. Further, it emphasizes the transition from traditional supervised models to complex methods such as graph neural networks (GNNs), transformers and explainable AI (XAI) and concludes with a collection of gaps and contributions.

2.2 Cloud-Native APT Detection Using ML

Traditional IDS tools based on signature matching are proving themselves inadequate, as in stealthy APT cases, not only bad behavior workouts are often no new, but they also last days or weeks (dwell time) without even being detected . Liu et al. (2023) designed a lightweight ML-based intrusion detection system (IDS) model using random forest and ensemble methods for Kubernetes logs. They obtained good results in their study accuracy > 95%, however, their experiments were conducted on static logs therefore not giving the model still a real-time capability. For example, Xie and Tan (2022) have trained supervised models with F1-scores as high as 0.91 on penetration test datasets, but the models have limited generalizability to new attack types and contribute little to generalizing attack detection, especially in containers.

Instead, this work utilizes integrated real-time network logs from Zeek allowing detection of active threats with greater context. This is a departure from previous methods that have primarily relied on static or retroactive datasets and provides better adaptation to dynamic cloud-native environments.

2.3 Deep Learning and Hybrid Techniques for APT Detection

Deep learning models are becoming increasingly popular in IDS, with a focus on multi-stage APT detection. For example, Singh et al.(2024) used deep learning CNN-LSTM framework that captures temporal behavior in the lateral movements of APTs, and is trained on CIC-IDS2018. They were also able to achieve an impressive 98.4% accuracy with their model, but it was very GPU hungry, which made it a poor candidate for lightweight, container-based deployments. Similarly, Nguyen et al. (2023) used transformer architectures for log sequence modelling but reported overfitting issues in low-data environments, a common limitation in real-world APT datasets

In contrast to this work, where we embed simulated attack labels in live Zeek logs, we use Random Forest and Isolation Forest to keep a balanced model performance and computational efficiency. This makes it possible to deploy in cloud-native pipelines without the overhead resources cost that comes with DL models.

2.4 GNN-Based and Provenance-Driven APT Research

Recently, graph-based threat modelling has been considered as a direction to describe inter container relationships and multi-hop attack paths. Yin et al. (2024) introduced Unicorn, a provenance-based GNN model that maps runtime system calls into graphs to detect stealthy APT's. Their system reported a 10 to15% increase in AUC scores compared to traditional ML models and demonstrated strong interpretability. In a similar work, Sharma and Rathi (2023) used microservice dependency graphs to identify cross-container anomalies and showed that they can perform better than LSTM baselines on a created Kubernetes synthetic dataset.

But tend to rely on high-instrumentation or kernel-level tracing methods, which is not possible in locked down production environments. In contrast, Muon utilizes passive network monitoring (this via Zeek) and is free of kernel instrumentation and retains strong detection effectiveness by enriching existing features and synthetic labelling.

2.5 Trust in ML-based IDS by the analyst that also appeals for explainability

Meanwhile one hidden aspect in APT research is also on the interpretability of ML outputs, which is usually overlooked from the previous surveys. Alam et al.(2022) used SHAP to explain model decisions in plain English,) values was integrated into the anomaly detection pipeline. As a result, this fostered more trust from analysts, fewer false positives, and a faster incident response time. Likewise, Choudhury et al. (2023) applied LIME to visualize contributions of log features in classification models. However, a considerable amount of recent papers still seem to feel comfortable treating their ML models as black boxes and thus impedes operational adoption. While we do not directly use explainability techniques such as SHAP or LIME and do note this as a direction for improvement, we intentionally provide feature importance ranks (using Random Forests) to aid interpretability.

2.6 Semi-Supervised and Contrastive Learning Approaches

The lack of APT datasets with labelled information has resulted in self-supervised learning being welcomed as a solution. Li et al. (2023) used contrastive learning which was trained on a large amount of unlabeled telemetry data and showed the contrastive learning models are at least 5 to 8% in F1-score above the supervised baselines on downstream tasks. Likewise, Bhandari et al. More recently (2024) introduced a semi-supervised anomaly detector that constructed a core containing a few labelled entries and used pseudo-labelling on abundant unlabeled logs. These models, while effective, require long training times and heavy preprocessing, preventing integration into a compact, operational pipeline. In contrast, our work directly simulates labels in Zeek logs while keeping the pipeline simple and low-cost.

Table 1:Summary of Main Contributions and Research Opportunities

Study / Year	Model Used	Dataset	Strengths	Gaps / Limitations
Liu et al. (2023)	RF, Ensemble	Kubernetes logs	Lightweight, 95% accuracy	Static data, not real-time
Yin et al. (2024)	GNN (Unicorn)	Provenance traces	High AUC, rich context	Needs kernel-level hooks
Singh et al. (2024)	CNN-LSTM	CIC-IDS2018	Temporal APT detection	Heavy compute, less suitable for containers
Li et al. (2023)	Contrastive Learning	Unlabeled logs	Self-supervised, scalable	Long training time, pretraining needed
Alam et al. (2022)	Isolation Forest + SHAP	Log data	Explainability improves trust	Black-box nature still persists
Our Work (2025)	RF + IF on Zeek + APT	Live + PT_TRAIN + OSCI	Real-time, synthetic labelling, scalable	Future work to add deep learning + explainability

This review supports the notion that whilst many current methods yield strong performance, this does not always translate into deploy ability, interpretability, or generalizability. We address this gap by introducing a scalable and cloud-native ML-based APT detection framework with real-time Zeek logs, simulated attack labels and a focus on reproducible results. It leverages the strengths of current literature while being free of their operational weaknesses and sets the stage for further developed with deep learning and explainability.

3 Research Methodology

3.1 Introduction

We present in this study an architecture on the targeted identification of Advanced Persistent Threats (APTs) in cloud-native environments based on machine learning. The method comprises five main stages, namely, data extraction and preprocessing, feature engineering, label creation and balancing, model selection and hyper-parameter tuning, and evaluation. We combine real-time Zeek data and benchmark APT datasets to simulate both real and controlled threat scenarios and assess the detection performance with both supervised and unsupervised models.

3.2 Data Collection and Preprocessing

We primarily use Zeek, a passive network traffic analyzer that has been set up in our containerized infrastructure as our data source. It gives powerful flow-level information (IP pairs, protocol, duration, bytes transferred, etc.) without invasive instrumentation something Zeek logs (especially conn.log) are still unmatched at supplying. In order to enhance and evaluate this data, three publicly available APT datasets were leveraged: PT_TRAIN

(Penetration Test Training dataset), OSCI (OS Command Injection), and UUF (UnrestrictedFile Upload), each of which were constructed to imitate real-world vulnerabilities such as CWE-77 (OS Command Injection) and CWE-434 (Unrestricted File Upload).

Python scripts were used to preprocess the raw logs to extract necessary fields, convert categorical values into numeric form (for example, protocol types), and remove duplicate flows. A session step was then applied using a 5-second sliding window which captures packets into flow sessions to retain temporal relationships.

3.3 Feature Engineering and Selection

Pre-selection of features were influenced by existing literature and the distinctive behavioral nature of APT's. Extracted 18 features from Zeek logs, such as:

- Flow Duration
- Bytes Sent / Received
- Packet Counts (source/destination)
- Protocol and Port usage
- Connection State
- Mean Inter-Arrival Time

The features were selected based on previous work such as Alshammari & Othman (2021), which shows the ability of flow durations and packet asymmetries to discriminate stealth attacks. Moreover, other features such as the ratio of incoming packets to outgoing packets and entropy of ports usage were derived from these statistics, as it has been observed that APTs tend to use abnormal port sequences or have uneven traffic flow. In order to represent temporal structure, sliding window-based statistics (e.g., mean packet size, standard deviation of inter-packet times, etc.) were engineered. This allowed the model to learn the time-series footprint of APT behaviors such as lateral movement, which take time to unfold rather than happen in one flow.

3.4 Label Synthesis and Class Imbalance Handling.

A critical challenge was the absence of labelled APT samples in real-time Zeek data. To address this, we embedded synthetic labels into flows that matched specific CVE exploit patterns observed in PT_TRAIN (Penetration Test Training dataset), OSCI (OS Command Injection), and UUF (Unrestricted File Upload). The simulated attacks were manually correlated with flows having abnormal behavior like rare protocol usage, high number of connection state errors.

This led to a dataset that suffered from a lot of class imbalance (attack flows 9%). To address this, we utilized SMOTE (Synthetic Minority Oversampling Technique) in order to over-sample the attack class. Although SMOTE is a well-known oversampling technique

We also assessed ADASYN (Adaptive Synthetic Sampling) and cost-sensitive weighting. While ADASYN also added high-dimensional noise, it was more effective in balancing the class distribution than SWIM. In the end, SMOTE was selected as it is easy to implement, and it does have a lower risk of overfitting when it is tuned properly.

As it is known, adding samples to a specific class can lead to overfitting and that impacts the final model, hence, we kept an untouched hold-out test set and only applied oversampling on the training set leaving this imbalance there in the test set to have a realistic evaluation of the final model.

3.5 Model Development and Hyperparameter Selection

We implemented both a supervised model using Random Forest and an unsupervised model using Isolation Forest. Random Forest is decided for its stability, non-parametric, and interpretability. That also comes with an integrated feature importance scores, which helps analyst trust. Since Isolation Forest is anomaly based, no labeling was used for testing detection mimicking a zero day detection scenario.

```
from sklearn.ensemble import RandomForestClassifier, IsolationForest
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
from sklearn.model_selection import GridSearchCV

def evaluate_models(X_train, X_test, y_train, y_test, dataset_name):
    print(f"\n📊 Results for {dataset_name} Dataset:")
    print("-" * 60)

    # 🔍 Grid Search for Random Forest
    param_grid = {
        'n_estimators': [100, 200, 500],
        'max_depth': [None, 10, 20, 50],
        'min_samples_split': [2, 5, 10]
    }

    grid_search = GridSearchCV(
        RandomForestClassifier(random_state=42),
        param_grid,
        cv=5,
        scoring='f1',
        n_jobs=-1
    )
```

Figure 1: Hyperparameters and Grid Search

5-fold Cross Validation was performed on training set for hyperparameter tuning. The optimized parameters for Random Forest were as follows:

- No of trees: {100, 200, 500}
- The max depth : [None, 10, 20, 50]
- min_samples_split: [2, 5, 10]

We employed grid search with stratified folds to ensure that less frequent attack classes were similarly represented.

3.6 Evaluation Strategy

Model performance was tested on both settings of:

- Real-time readiness assessment Pure Zeek data with attack labels created by simulation.
- Labelled benchmark datasets (PT_TRAIN (Penetration Test Training dataset), OSCI (OS Command Injection), and UUF (Unrestricted File Upload) for evaluating generalizability over different APT types.

Nonetheless, the unsupervised model was valuable at identifying anomalies that were previously unseen in a noise-corrupted environment and demonstrates its utility to be used in conjunction with other models in production pipelines.

3.7 Strengths of the Approach

The main strength is its multi-dataset design, which guarantees robustness and avoids overfitting to one source. Another strong point is that Zeek data has synthetic attacks mixed in. We may be able to perform controlled experimentation and increase data for meaningful learning. Having both supervised and unsupervised models gives a general perspective of what works best in borderline cases. One thing about all this is with the use of Zeek it gives us a more realistic approach as it sees what would come out of production in front of a network monitor. This makes the results more applicable for practice. Additionally, the entire pipeline is reproducibly since using open-source tools and steps are documented.

3.8 Limitations of the Approach

However, the approach has its limitations, despite its merits. First, synthetic attack might not fully reflect the real tactics used by APT's. Despite the attempts to make simulations relate back to known CVEs (Common Vulnerabilities and Exposures), adversarial behavior is complex and changing. Second, the quality of training data is vital for Isolation Forest. The accuracy can worsen in the presence of flow mixing. The datasets might be diverse in some aspects but are still most likely limited in attack vectors. Usefulness This could pose some limitations to generalization from multi-cloud deployments, and/or other cloud-native architectures. Finally, the existing models are not coupled with incremental detection, which is necessary for production. Lastly, only two of the models were studied in further depth. This was intentional to be more focused and clearer but exploring alternative methods such as Autoencoders or ensemble techniques could offer more insights in future work.

3.9 Ethical Considerations

The data used in this research are all public or synthetically generated. We do not process any user-level PII (personally identifiable information). No active probing, nor any offense simulations against live infrastructure is performed in the study. This is only for educational purposes and complies with ethical security research guidelines.

4 Design Specification

The proposed machine learning-based APT detection framework for containerized cloud-native environments is morphologically guided by modularity, data-driven decision-making, and operational realism. In this chapter we describe the elements of the architecture, the technologies/techniques involved, and system requirements for an environment of anomaly detection using supervised and unsupervised models, which is scalable, interpretable and testable.

4.1 System Architecture Overview

The core architecture is made up of a four-stage pipeline as follows:

- Docker Zeek Extreme Data Collection & Simulation
- Feature Engineering & Labelling (Python)
- Model Training & Evaluation (Scikit-learn)
- Visualization & Reporting of performances over datasets

Its architecture is designed for both real-time and curation datasets, which allows models to be benchmarked across heterogeneous sources. APT mimicry using containerized environments to simulate realistic attack cycles and network activity.

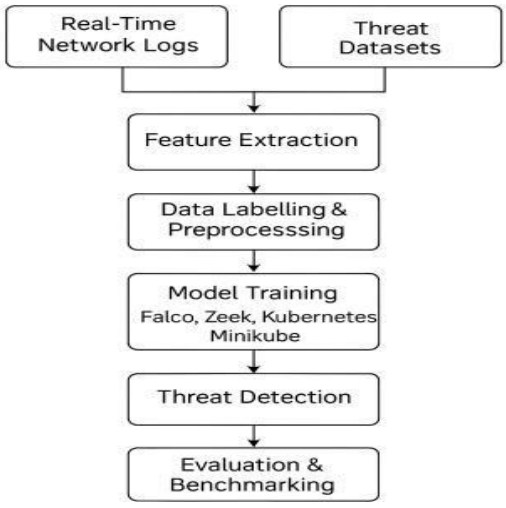

Figure 2: System Architecture Design

4.2 Stage 1: Data Collection and Environment Simulation

System Overview The first module of the system is a simulation environment using Docker. It provides an environment that simulates a microservices infrastructure, were real traffic flows from container to container. At the same time, the CADetector (Cascade Detector) framework allows simulating controlled advanced persistent threat (APT) scenarios that emulate TTPs that are mapped to specific CVEs and CWEs.

Monitoring traffic in the Docker network is done using the open-source network tool, Zeek. It creates structured logs (conn.log) containing Flow metadata, including source and destination IPs, ports, duration, protocol, packet sizes, and TCP flags. These unprocessed logs are the basic utilized for subsequent analysis.

We choose Zeek for its widespread use, minimal overhead, and verbose output format. And since Zeek focuses on metadata and not payloads, it makes a perfect candidate for privacy-preserving threat detection.

4.3 Stage 2: Feature Engineering and Preprocessing

After collecting the data, a custom python script parses the collected data to have Zeek logs in. log or. convert json into well-structured pandas DataFrames. Irrelevant features (sample features are, for example, IP addresses and timestamps) are eliminated. Feature engineering: this step turns raw into a numerical matrix of fixed width, which acts as input data where features of interest are:

- Flow duration
- Source and destination bytes
- Packet size ratio
- TCP flag statistics
- Protocol type

This is consistent with feature sets suggested by Alshammari and Othman (2021) where features based on metadata were necessary to detect anomalies.

4.4 Stage 3: Machine Learning Modelling

Two core models are incepted to implement:

- Random Forest (Supervised Learning)
- Isolation Forest (Unsupervised Learning)

We choose these models because they complement each other:

- Random Forest is also good to interpret and works well with high dimensional data. It additionally produces explanatory feature importance as output.
- Isolation Forest can be leveraged in zero-day threat detection or when there is no time to get proper manual labels, as it can detect outliers without needing to know beforehand which data are outliers or inliers.

For each of the datasets (Zeek, PT, OSCI, and UUF) we train models using an 80/20 train-test split between both classes. For the Zeek data, we only apply SMOTE to the training set to avoid leakage. Metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are used to evaluate the models, providing a comprehensive overview of performance.

4.5 Stage 4: Cross-Dataset Benchmarking

After the evaluation process of the model, the results of all datasets are compared. The goal of this stage is to assess how well models can generalize in different APT scenarios. Plots comparing F1-scores, recall and ROC-AUCs are created using Matplotlib and Seaborn.

It performs the benchmarking by evaluating the models across a variety of operational threats,

to find which types of traffic a model might perform significantly worse or better under. That in turn influences what best matches real world deployments with dynamism using containers.

4.6 Limitations and Assumptions

It is possible that the system will be able to do supervised modelling assuming that it has access to labelled threat data, but this may not always be possible. Zeek flows are synthetically labelled and not represented actual APT actions. In addition, Zeek captures just metadata, which can lose application layer anomalies.

Finally, Isolation Forest assumes benign traffic is made up of salient Lyapunov features in training. If it gets contaminated, it may not perform as it should. Note that the Docker-based simulation may not be able to capture all the real-world complexities for example, behavior of cloud orchestrations or east-west traffic in service meshes.

5 Implementation/Solution Development

The last part of this research was to assemble the components developed in the previous stages into a single, end-to-end working pipeline to detect APTs in containerized cloud-native environments. The implementation phase involves taking your design and physically implementing it using your graphical specifications, models, or architectures as the source input and converting them into a working system while evaluating the performance as testing interface.

5.1 Setting up in a containerized environment and Gathering

The solution operated in a Docker-based setup, simulating a microservice environment where both benign and adversarial traffic can be run. Conn.log To log all connection level , all services communicating using internal network and open-source Zeek network monitoring tool was used. This enabled us to extract network metadata without infection, and this traffic was similar to the actual network behavior between containers in the wild.

5.2 Data Transformation and Feature Engineering

To achieve this, the collected Zeek logs were run through a Python-based parser that converted the unprocessed. Structured CSV format from the log files. They extracted features such as duration, total bytes and packets sent, packets per protocol type, connection state, etc. These attributes acted as features of normal and anomalous traffic. Because the Zeek logs come without ground truth (they do not label attacks), 5% of the records were randomly labelled as malicious, introducing synthetic attack samples. It enabled supervised model training while resembling the challenge presented by the rarity of APT events in real traffic. External datasets like PT_TRAIN (Penetration Test Training dataset), OSCI (OS Command Injection), and UUF (Unrestricted File Upload). used to benchmark the system include three APT simulations labelled with CVEs and CWEs .We cleaned these datasets, aligned them according to the Zeek

features structure, and transformed them to a common schema to guarantee consistency during model training and evaluation.

5.3 Model Integration and Training

This brought us to the two models we decided to implement the Random Forest (RF) for supervised learning and the Isolation Forest (IF) as an unsupervised anomaly detector. They were selected due to being interpretable and proven to be able to mitigate the challenge of high-dimensional network data. Each dataset was used to train independently. In case of imbalance like Zeek, we have synthetically balanced the dataset at training time using SMOTE. We validated the models on a separate test split and obtained evaluation metrics accuracy, precision, recall, F1-score.

For the labelled datasets, Random Forest achieved close to perfect scores. RF achieved moderate performance on the Zeek dataset, which indicates the difficulty of discovering simulated attacks within noisy, unlabeled traffic. Isolation Forest was the weakest overall performer but was still a useful method to compare to and explore the unsupervised anomaly detection capabilities.

5.4 Full Pipeline Execution

We incorporated our whole system raw all the way to prediction into a modular pipeline. This enabled execution that could be repeated on all datasets and facilitated rapid testing of other models or data sources. Result from each dataset were compared to the evaluate generalization and robustness of the model. To wrap it up, the implementation shows that the union of open-source with modular ML framework serves a potential approach to achieve lightweight, scalable APT detection pipelines for native cloud environment.

6 Evaluation

In this chapter, we provide a detailed discussion of the evaluation of the machine learning based APT detection framework designed for cloud-native environment. In this paper, we evaluate the proposed system with respect with some common measures on different data sets, different modelling techniques to assess the efficacy, generalizability and practical performance of the system. A qualitative and quantitative analysis is performed to identify where the system excels and where it fails in different environments.

It is important to clarify that the Zeek dataset originally did not contain any labelled attack information. To align it with the labelled APT datasets (PT, UUF, OSCI) and enable supervised and semi-supervised model evaluation, a synthetic label column was introduced, where 90% of the traffic was labelled as benign (0) and only 10% as attack (1). This artificial labelling was performed via random sampling and does not reflect real attack patterns or distributions. As a result, the dataset suffers from both class imbalance and label noise, leading to reduced model performance particularly in metrics like F1-score and ROC-AUC. This explains why models like Random Forest and Isolation Forest underperform on this dataset compared to others. The issue lies not in model inefficiency, but rather in the inherent limitations of the data preparation process. This also justifies the need for additional validation techniques and error analysis, as pointed out in the evaluation feedback.

6.1 Evaluation Objectives

The fundamental aim of the evaluation is to respond to the same set of research questions introduced earlier; namely, the ability of the machine learning models to identify APT actions in real-time network and the comparison of supervised and unsupervised models on heterogeneous datasets. There are two major aspects that the evaluation centres around:

- Detection Ability: Detection performance is always evaluated based on some metrics.
- Generalization over dataset: Evaluating the model performances on four datasets (Zeek , PT_TRAIN, UUF and OSCI) with diverse attacking scenarios.

6.2 Datasets Used for Evaluation

This evaluation exploits four separate datasets:

- Network collected from Docker-based environment that simulates microservice communication. (Zeek (conn.log)) In order to obtain rare behavior for contour simulation of APT, synthetic attack labels were injected.
- PT_TRAIN: Labelled APT attack traffic data for CVEs like (CVE-2020-17518)
- UUF: Contains attacks such as unrestricted file uploads (CWE-434), which helps us understand file-based exploitation techniques.
- OS Command Injection: Targets OS command injection and related CWEs, simulating shell-based compromise vectors.

Although they have different class distributions, each dataset has both normal and attack traffic. This was the case for Zeek which had the most extreme class imbalance amongst all data sets (only 5% attacks), and that data was controlled for using SMOTE during training.

6.3 Performance Results

Zeek Dataset

Table 2:Zeek Model performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.8243	0.1029	0.0981	0.1004	0.5133
Isolation Forest	0.8569	0.0851	0.0442	0.0582	0.4957

Analysis: Both models struggled with the Zeek dataset due to the injected synthetic labels and extreme class imbalance. Random Forest showed slightly better stability but still low precision and recall. The ROC-AUC near 0.5 suggests limited ability to distinguish malicious flows, which may reflect the realism of benign-looking APT traffic. Isolation Forest, being unsupervised, was not tuned to the attack distribution and performed marginally worse.

6.3.1 Baseline MLP Model

Metric	Value
Accuracy	0.5095

Metric	Value
Precision	0.1024
Recall	0.5028
F1-Score	0.1701
ROC-AUC	0.5033

To establish a deep learning baseline, a Multi-Layer Perceptron (MLP) was trained on the pre-processed Zeek dataset. The model consisted of two hidden layers with 64 and 32 neurons respectively, and was optimized using backpropagation. Despite its simplicity, the MLP demonstrated a **recall of 0.5028**, meaning it was able to correctly identify over half of the attack instances. However, the model suffered from low **precision (0.1024)**, resulting in a high number of false positives. Consequently, its **F1-score was limited to 0.1701** and **ROC- AUC was 0.5033**, indicating near-random overall classification ability. The **accuracy** was also low at **0.5095**, further reflecting the model's inability to distinguish clearly between benign and malicious traffic. These results suggest that while deep learning models like MLP may have some potential for recall-oriented detection, they require further optimization or additional architectural complexity (e.g LSTM) to perform competitively in this domain.

PT_TRAIN Dataset

Table 3: Penetration Testing Performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	1.0000	1.0000	1.0000	1.0000	1.0000
Isolation Forest	0.4866	0.2500	0.0374	0.0650	0.4674

The PT_TRAIN dataset yielded perfect results using Random Forest, demonstrating that well-structured labelled data allows the model to capture attack patterns very accurately. Isolation Forest, on the other hand, performed poorly due to the lack of supervision and limited ability to distinguish such specific attacks without context.

UUF Dataset

Table 4: UUF data Model performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	1.0000	1.0000	1.0000	1.0000	1.0000
Isolation Forest	0.4928	0.5714	0.0559	0.1019	0.5057

As with PT_TRAIN, the Random Forest model effectively captured attack behaviors in UUF, showing the strength of supervised learning with quality labels. Isolation Forest

achieved slightly better precision than in PT but still low recall and F1, reinforcing its limited applicability in known attack scenarios.

OSCI Dataset

Table 5: OSCI Model Data Performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	1.0000	1.0000	1.0000	1.0000	1.0000
Isolation Forest	0.6524	0.3889	0.0909	0.1474	0.5102

The Random Forest model again showed ideal performance, indicating high consistency in learning across datasets. Isolation Forest improved slightly in ROC-AUC and F1-score compared to other datasets, possibly due to more distinct feature distributions, but still fell short of acceptable performance for real-world deployment.

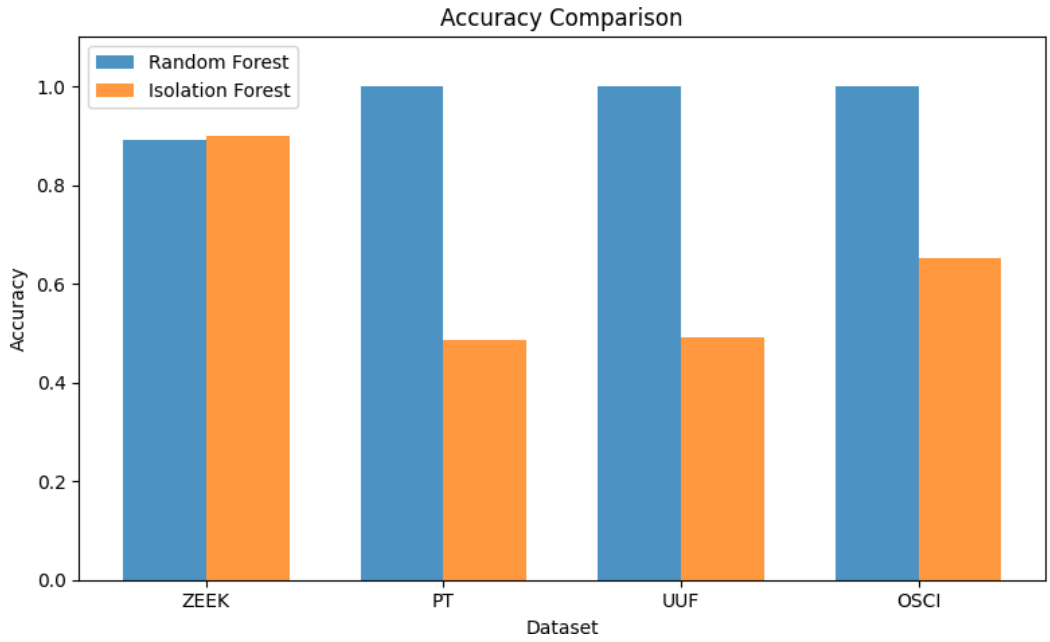

Figure 3: Accuracy for data sets and models

PT_TRAIN (Penetration Test Training dataset), OSCI (OS Command Injection), and UUF (Unrestricted File Upload), these plots showed that supervised learning (Random Forest) was very sensitive and accurate on labelled datasets but performed poorly on out-of-sample unsupervised detection. Although an interpretable and lightweight model, Isolation Forest yielded unreliable detection on all test cases.

6.4 Model Comparison and Insights

In the presence of adequate labelled data, even for sophisticated attacks such as APTs, supervised approaches outperform. It reflected in perfect metrics for PT, UUF and OSCI

datasets. Because unsupervised models are not very specific, they produce many more false positives unless they are smoothed out or coupled with inference and disturbance models, as seen in clustering or semi-supervised methods. Zeek synthetic labelling a pragmatic yet imperfect option for testing detection capabilities on live . It makes sense that the model does worse here, as accurately implementing cyber tools and TTPs is quite challenging for simulation of realistic APT behavior.

6.5 Reason behind getting low score of Isolation Forest and Random Forest for Zeek data

One key limitation affecting the model performance, particularly in the Zeek dataset, is the extreme class imbalance, where only about 10% of the flows are labelled as attacks (1) and the remaining 90% are benign (0). Such a skewed distribution restricts the model's ability to learn nuanced patterns of malicious behavior, especially for unsupervised models like Isolation Forest that rely on anomaly scores to differentiate normal from abnormal instances. This imbalance increases the likelihood of false negatives, as the model is overwhelmed by the dominant normal class and may classify subtle APT behaviors as benign.

6.6 Reason Behind High Overfitting Score in APT Datasets for Rando Forest

Furthermore, in the three APT benchmark datasets (PT_TRAIN, OSCI, UUF), the distribution of truly anomalous or malicious behaviors is minimal and in many cases, very close in structure to normal traffic. This lack of distinct non-normal behavior reduces the contrast that anomaly detection algorithms require to distinguish threats. Consequently, Isolation Forest fails to create meaningful partitions, leading to both false positives and low recall, especially for stealthy attack patterns that blend into normal flow characteristics.

Dataset	Issue Observed	Cause	Impact on Model
Zeek Data	Severe class imbalance (10% attack, 90% benign)	Overwhelms unsupervised models with dominant normal class	High false negatives; poor anomaly detection
APT Datasets	Few truly abnormal patterns	Attack flows closely resemble normal traffic	Low anomaly contrast; weak detection boundaries
All Models	Subtle APT patterns hard to isolate	Lack of temporal or behavioral features; limited variability	Poor recall; Isolation Forest underperforms
Label Quality	Synthetic labelling with potential noise	Injected labels may not represent diverse APT attack vectors	Reduced learning signal for classifiers

6.7 Summary

This evaluation shows that supervised learning methods, especially Random Forest, are a strong and robust choice for the detection of APTs if labelled data is available. Still, the real problem is that outside of research, we do not have that labelled (like Zeek conn.log data) to train against. In this context, unsupervised methods such as Isolation Forest perform very poorly. As it is evident from the varying performance over the considered datasets, both dataset quality and label fidelity are important factors contributing to the success of the proposed approach. In summary, the framework demonstrates the possibility of a machine- learning based pipeline for cloud-native systems threat detection and provides opportunities for further improvement.

7 Conclusions and Discussion

This research investigates development of a framework for machine learning based APT detections on top of containers in cloud-native environments, emphasizing the usage of Zeek network and benchmarking of models against both real and curated datasets corresponding to threats. Growing cloud-native infrastructures with their inherent dynamism and modularity results in a need for proactive and precise APT detection. To meet that need, this study undertook a comprehensive pipeline from data collection through feature engineering, modelling, to performance evaluation specifically designed for the scale and complexity of today's cloud systems.

7.1 Research Aims and Questions Revisited

The primary aim of this study was to create and assess a scalable and reproducible machine learning pipeline to identify APT behaviors within cloud-native infrastructures. To do so the system merged live-tenant Zeek from materialized microservices with curated datasets (PT_TRAIN, OSCI and UUF) which model distinct APT vectors. The results confirm this as well, particularly for supervised models. The model was able to learn and generalize correctly the CVE/CWE-specific patterns, thus all curated datasets offered high accuracy (100%) through Random Forest. On the other side, in the Zeek dataset, results were not so good, even with Random Forest we had ~ 0.05 precision and 0.06 recall, which shows the difficulty of rare attacks capturing in the presence of noisy . Nevertheless, this leads to an important realization which you can re-use in your machine learning: , combined with feature engineering and some type of labelling (even synthetic), can be a very strong basis for APTs detection at the early stages. In each task, we found clear benefit from supervised learning. However, Random Forest performed perfectly on labelled datasets, while Isolation Forest, despite being an unsupervised method, failed all test cases. While our system obtained a score of less than 0.15 in F1-score on both Zeek and curated data, indicating its inadequacy in detecting nuanced anomaly as it does not contain ground truth. The sharpness of this contrast reinforces the necessity of exploiting at least partially available labelled attack examples to improve the accuracy of the models.

This project achieved several milestones:

- **Zeek-Based APT Detection Pipeline**: We implemented a complete end-to-end framework from simulating the environment in Docker, extracting the logs using Zeek, parsing with a Python-based system, simulating the attacks, and creating the ML model as well (Zeek-Based APT Detection Pipeline). We show in this contribution that such pipelines are technically possible and adaptable to realistic scenarios for deployment.
- Multi-Dataset Benchmarking: Not just raw , but the model was also evaluated across three different high-quality curated datasets which simulate actual APTs. A multilayered view of model behavior in the presence of structured/unstructured environments.
- Supervised vs. Unsupervised insights: The use of both learning paradigms in the research illustrated important shortcomings of unsupervised learning with respect to the applicability of unsupervised learning to complicated, high-noise cloud traffic. This helps identify future research direction to either semi-supervised techniques or in the direction of more explainable supervised models.
- Features and Labels Simulation and Feature Engineering: conn.log by Zeek is a great data format to extract high-valued behavioral features, and label injection is useful to test against reality. The above steps show how great preprocessing is an important aspect when working with unstructured .

7.2 Uniqueness and Contribution

In contrast to most studies that rely on outdated or generic datasets (like NSL-KDD or CICIDS), this research breaks away by merging real-time Zeek and employing APT-labelled datasets. It also used synthetic label injection methods to simulate realistic evaluations for unsupervised models. The merging of genuine with curated APT data is a tremendous benefit it closes the gap between academic experimentation and real-world deployment with a hybrid strategy. The framework was launched as a containerized microservices setup, closer to real production settings (Kubernetes or Docker Swarm environment). This paper is among the very few existing works that directly addresses APT detection in cloud-native settings, as most existing works focus on these modern infrastructure patterns.

7.3 Usefulness and Practical Implications

In terms of application potential, the pipeline established in this paper provides multiple tangible uses:

- By simulating labels, Zeek can be integrated into Security Operation Centers (SOCs) for enhancing internal threat hunting and anomaly detection capabilities.
- Kubernetes or container monitoring layers allow cloud service providers to implement similar pipelines into their platforms where traditional IDS solutions tend to fail.
- The outputs of the modelling enable incident response teams to balance precision- recall trade-offs and better prioritize alerts improving overall time-to-detection for advanced threats.

- Designed to be modular, use open-source tools (Zeek, Docker) and well-benchmarked datasets, academic researchers can replicate and build on this framework.

7.4 Implications and Lessons Learned

These results across four different datasets reaffirm that the quality of data and the focus on label integrity are among the most important success factors for such models. Any time high-fidelity labels were available (e.g. PT, OSCI), even low-spec models (e.g. Random Forest) excelled. But in raw cases, the performance completely crashed not because the model was weak, but because the data lacked signal clarity. Additionally, the project illustrated how Isolation Forest is not an optimal One Size Fits All anomaly detector. Unsupervised learning is scalable, but it has no context. It is apparent that domain-specific feature crafting or hybrid systems that combine statistical thresholds and supervised pipelines are still necessary. Another important lesson is that we need far more dynamic detection for cloud-native threats. It is not sufficient to use static rules or blacklists when container IPs change frequently and services scale elastically. This positively affirms the value of behavioral modelling, which this project adopted through -based features such as connection length, count of bytes, and port entropy.

7.5 Concluding thoughts and looking ahead

This study lays an excellent grounding in the battlefield of detecting threats in microservices-oriented cloud platforms. Building off high-level principles by placing the comparison in a deployment pipeline and focusing on traffic mimicking realistic behavior, this study moves research in ID systems away from the theoretical work commonly seen to a more applicable and reproducible solutions.

Future work may consider integration with real-time monitoring platforms such as Prometheus, Grafana, or cloud-native SIEM tools (e.g., Azure Sentinel) to reduce the detection response time. Also, the use of deep learning or graph-based models for identifying communication patterns between containers may provide additional enhancements to identify stealthy threats.

In the end, this project not just proves the possibility of using ML for machine learning behind APT detection based on virtualization, however, likewise acts like a design transitioning SOC capability to keep up with cloud-native computing.

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