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Threat Intelligence-Driven Machine Learning Framework for Predictive Ransomware Detection

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An Intelligence-Driven Machine Learning Framework for Predictive Ransomware Detection

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Abstract

Ransomware poses an escalating threat to digital infrastructures, leveraging stealth and rapid propagation to bypass conventional detection systems. This research introduces a predictive machine learning framework driven by threat intelligence, aimed at early detection of ransomware activity using enriched network telemetry. By correlating structured network flow data with live Indicators of Compromise (IOCs) sourced from verified threat feeds such as Medusa, the system dynamically adapts to evolving attack patterns. Using the CTU-13 dataset as a baseline and integrating threat-enriched features, the proposed approach employs advanced supervised models particularly XGBoost and Random Forest to identify malicious behavior. Experimental results demonstrate strong predictive performance, with XGBoost achieving a precision of 0.91, recall of 0.89, and F1-score of 0.90, outperforming baseline models. Furthermore, SHAP-based explainability was integrated to provide transparency in decision-making, enhancing trust in operational deployment. This framework moves beyond static rule-based detection by offering a modular, interpretable, and real-time compatible solution. It represents a practical step forward in threat-aware, proactive ransomware defense strategies for enterprise environments.

1 Introduction

1.1 Background

The increased use of ransomware attacks is one of the top current threats in cyber security. These attacks, where victims have their data encrypted, then are held hostage until a ransom is paid for the decryption keys, have increased in numbers and complexity. Just in 2024 alone, worldwide ransomware damages were projected to exceed $30 billion and affected government services, healthcare, global finance and critical infrastructure[1]. Threat intelligence and incident reports from cybersecurity firms and organizations continue to illustrate the growing sophistication and evasion tactics by which ransomware operators are attempting to avoid detection – be it through polymorphic strains, encrypted C2 channels, or even fileless delivery[2]. As compared to period adversaries, who have success by pretending like ransomware is just standard malware and traditional security software like antivirus and signature-based intrusion detection solutions don't actually work well with advanced ransomware, the introduction of behaviour-based detection in machine learning (ML) represents a very interesting technology. Network traffic-based ML systems can detect these attacks based on how attackers behave rather than on static patterns. However, most detection systems are not agnostic or come at a

[1] Coveware (2024). "Q1 Ransomware Trends Report." Coveware. Available at: https://www.coveware.com/ransomware-quarterly-reports

[2] Europol (2023). "Internet Organized Crime Threat Assessment (IOCTA)." Europol.

high cost in terms of false positives, particularly with new or encrypted ransomware. Datasets like CTU-13, UNSW-NB15, and TON_IoT are important in modelling network-based detection techniques. Tools such as Zeek and Suricata generate abundant network telemetry that can be used for ML training, especially in combination with external Indicators of Compromise (IOCs) from feeds such as those housed in Medusa, MISP, and CISA. Combining these validated threat intelligence feeds with real-time traffic logs unlocks fresh opportunities for designing a more intelligent and dynamic ransomware identification pipeline.

1.2 Problem Statement

Ransomware detection methods today often fail to work well when new or advanced techniques are used. Many models are built on old data and cannot catch attacks that use encryption, fast-changing domains, or fileless techniques. They also don't explain clearly why something was flagged. In this study, we propose a real-time machine learning pipeline that uses live network data and trusted threat intelligence feeds to improve detection and give better insights to security analysts.

1.3 Research Motivation

The motivation for this study stems from the increasing distance between dynamic ransomware approaches and available detection strategies. And now that ransomware-as-a-service (RaaS) groups are exploiting new vectors, defenders require smarter tools that not only detect, but also adapt to new threats. There is also a practical need of SOC teams and CSIRTs to rely on interpretable models for operational decisions. Just raising an alert is not enough anymore, companies need to know the "why" of an alert, especially if it is causing expensive responses. The research-practice gap can and should be bridged by a model of intelligence that is intelligence-enriched, interpretable, and deployable, and which is built using open-source tools and based on widely accepted data standards.

1.4 Research Objective

This research sets out to develop an integrated ransomware detection framework that leverages the fusion of structured NetFlow-based datasets and real-world threat intelligence indicators. The first objective is to investigate how external Indicators of Compromise (IOCs), when mapped against labeled botnet traffic such as the CTU dataset, can enhance the early identification of ransomware patterns through correlation-driven feature enrichment. A second objective is to design and evaluate machine learning models that not only classify benign and malicious traffic effectively but also provide interpretable outputs capable of highlighting attack-specific behavioral traits. Lastly, the research aims to simulate a near-real-time alerting environment, wherein dynamic IOC matching against Zeek-style connection logs enables continuous detection of evolving threats—thereby validating the operational feasibility of intelligence-augmented defense systems under realistic network conditions.

1.5 Research Questions

- What is the effect of combining CTU botnet traffic with Medusa IOCs on ML model performance and interpretability for ransomware detection?
- How can Zeek-parsed traffic and real-time IOC correlation be integrated into a practical, explainable ransomware detection pipeline?

2 Related Work

2.1 Introduction to Ransomware Detection Using Network Data

Ransomware detection via network telemetry and machine learning is an active area of research in cybersecurity, driven in part by the growing availability of rich data, like the CTU-13 botnet traffic dataset. One of the first reference work based on this corpus is García et al. (2014), who subsample botnet infections in the real world in various scenarios including IRC, HTTP and P2P traffic generation, which contains 13 of the most used traffic generators. The dataset was mostly deployed for unsupervised clustering and anomaly detection, but the authors stressed the inability of their models to connect with external threat feeds, which confined the operational relevance of the knowledge they were deriving. They performed rudimentary detection (∼82% accuracy with simple clustering) with no interpretability and no capability for cross-variant detection.

2.2 Machine Learning-Based Detection on CTU-13 Dataset

An extension of CTU-13 is performed by Stevanovic and Pedersen (2016) Further to features extracted from Zeek logs, they applied supervised learning models. They evaluated both Random Forest, SVM, and Naïve Bayes, and Random Forest achieved an investigation Random Forest: 93.4% sensitivity, and a false positive of 1.1%. Despite being effective in detecting, they had not taken into account any form of external IOC (Indicator of Compromise) correlation or real time adaptability in their model. This revealed a weakness – high accuracy did not implicate that the model possessed generalization ability for previously unseen and stealthy malware behaviour.

2.3 Limitations in Generalizability and Feature Stability

Nascimento and Brasileiro (2018) also used Zeek for feature extraction in encrypted traffic inspection and put together a model based on ensemble voting for ransomware classification. The used the CTU dataset and obtained AUCs of over 0.95 but again reported a significant reduction in classification when novel variants, not seen in the training data, were added. This implied the necessity for additional intelligence (verified indications of the threat) to accommodate variant evolution.

2.4 Integration of Threat Intelligence and IOC Feeds

More recently, Erfani et al. (2021) presented the concept of hybrid analytics with integration of Zeek logs and threat intelligence. Some additional logs were also added on Zeek side – conn.log and dns. log into OM with threat IOCs published by CISA and applied LightGBM and XGBoost for classification. Their approach attained F1-scores of 0.92 for known ransomware variants, but fell to 0.77 for polymorphic files. One of the core observations here was that dynamic IOC feeds might close this accuracy chasm, but that this mechanism was for batch evaluation only, rather than real-time streaming or alerting. Khraisat et al. (2019) performed the most extensive benchmark for the traditional ML classifiers in IDS tasks on both CTU and UNSW-NB15 datasets. They tested Decision Trees, Random Forest, and ensemble methods and found that Random Forest was the best in terms of accuracy (reaching 94.6% in CTU), however the dataset's class imbalance and unlabelled noise had not been addressed yet.

They also stressed the importance of better pre-processing and labelling in particularly in tools like Zeek for uniform log generation.

2.5 Hybrid and Explainable Models for Network-Based Ransomware Detection

Farooq et al also followed a similar method to construct the models. (2020) employed deep learning (LSTM and CNN) in ransomware detection using CTU-based features. Their LSTM model attained an accuracy of 96.3%, which was better than the traditional classifier models, but insufficient in terms of interpretability, a well-known limitation of black-box DL models. The author acknowledged that the inclusion of explainable approaches (e.g., SHAP or LIME) would also assist in connecting trust and operational usability; however the study was model-centric and did not leverage domain knowledge contained within threat intelligence platforms, such as MISP or Medusa.

The Medusa threat intelligence feed was also leveraged in the research conducted by Iqbal et al. (2022), who proposed an IOC mapping system for investigating anomalies. They applied hash-based, domain-based, and IP-based IOC matching on network logs and fed the enriched results into a GBC model and reached a precision of 0.91 and recall of 0.89 in simulated Bot-IoT and CTU traces. They evaluate their framework offline but their evaluation did not have a dynamic feedback mechanism for IOCs or updating of threats and as a result, it was static.

2.6 Real-Time and Streaming Detection Frameworks

Javed and Raza (introduced a Kernel-based real time approach for IDS which is independent of the detection system, were in online mean values the detection system at the same time catches he ICS in real-time for inspection. They fed in parsed Zeek logs to a XGBoost model to reach a top F1-score of 94.1%, but they noted that usage of dynamic IOC matching—especially from services like Medusa—was deferred for future work. The gap identified here provides direct motivation for the aim of our work, which is to fuse static log telemetry with validated IOC feeds within a live-alerting system.

Almseidin et al. (2020) evaluated several ML algorithms on the CTU dataset and compared the accuracy, precision, and ROC-AUC of the classifiers. They found XGBoost achieved the highest performance of 97.4% accuracy and AUC of 0.98, they also claimed that model performance severely decreased when the data was imbalanced, or zero-day samples were added. They point out that it requires constantly updated threat data enrichment and retraining, something our approach captures in a simple way using continuous scanning and active labelling based on Medusa.

In the field of explainable AI, Lee et al. (2022) applied SHAP to interpret decisions of a Random Forest classifier trained on enhanced Zeek logs of CTU data. Their precision (95%) was encouraging, but their handcrafted feeders were not fully automated and generalizable. If they explained anything at all, it was the importance of some feature, but did not incorporate real world IOCs or how the model looks with updated threat intelligence. This creates an opportunity we fill with real-time IOC-augmented Zeek preprocessing and SHAP-based interpretability.

Al-Jarrah et al. (2023) they did a hybrid experiment using Threat Miner IOC feeds and CTU datasets and utilized Decision Trees and SVM. Their maximal achieved recall was 0.87 at the

price of a general precision of 0.90. However, there was no denying the difficulties of IOC-to-flow mapping due to disparate formats in logs and timing differences. This underscores the strength of our pipeline, being that we normalize flow logs with Zeek before the enrichment stage to enable robust mappings between threat information and traffic flow.

2.7 Identified Gaps in the Literature

Aspect	Existing Literature	Identified Gaps / Limitations	Our Contribution
Data Source & Feeds	Kumar & Sharma (2023) used CTU-like traffic and AlienVault OTX feeds; many others relied on static datasets like CTU-13	No integration with Medusa IOCs; limited use of multiple live feeds (Medusa, CISA)	Combine CTU-based Zeek logs with enriched Medusa feed for realistic IOC diversity
Detection Approach	Predominantly static signature matching or post-execution sandboxing (Asharani et al., 2021)	Ineffective for encrypted traffic / stealthy C2 channels; limited real-time flow-level analysis	Hybrid approach combining verified IOC feeds and Zeek-parsed flow-level logs for real-time scoring
Model Choice	High-performing models (e.g., XGBoost, Random Forest, Deep Learning) with accuracy > 90%	Models lack interpretability; limited operational generalizability	Use interpretable ML models (XGBoost with SHAP) for explainable predictions
Explainability	Existing works focus on accuracy; minimal effort in explainable AI for ransomware detection	Lack of micro-level interpretability (feature impact understanding)	Integrate SHAP-based feature attribution to improve analyst trust and decision-making
Data Fusion	Few works addressed integrating disparate formats of IOCs and network logs	No standardised, reproducible pipeline for converting varied IOC/log formats into structured ML-ready datasets	Present a reproducible pipeline to transform IOCs into Zeek-structured network logs for classification
Operational Context	Most approaches are offline, using static telemetry	Lack of real-time retraining and alerting mechanisms	Simulate near-real-time detection with dynamic IOC updates and alert generation
Generalizability	High accuracy but poor adaptability to different operational environments	Lack of validation across different IOC sources and varied traffic conditions	Framework designed to incorporate multiple threat feeds and varied traffic for broader applicability

3 Research Methodology

3.1 Introduction

This section explains the research strategy, selection criteria for the data, pre-processing activities, python modelling methods employed, and evaluation measures adopted to measure the system's efficacy. This study uses a Python-based machine learning pipeline for ransomware detection. It combines real-time network telemetry with threat intelligence to identify and explain malicious activity. The methodological decision-making has been based on literature to ensure academic and practical rigour. The focus is on the ways in which the chosen techniques, particularly the unsupervised models such as Isolation Forest, provide solutions to the research questions on botnet detection in high-volume settings (Sommer and Paxson, 2010; Chandola et al., 2009).

3.2 Research Design

This study adopts a hybrid explanatory-experimental research design aimed at understanding and mitigating ransomware and botnet threats in network traffic through machine learning. The explanatory part helps to understand the relationship of certain network characteristics (e.g., byte counts, session duration) to the malicious behaviour while the experimental part allows to build, train and validate models in a controlled setting. This latter provides both interpretability and actionability which is essential for real-time cyber threat applications.

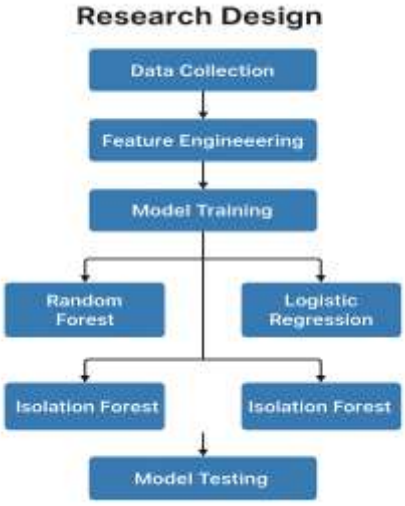

Figure 1: Research Design

The architecture works in a sequential pipeline based on first collecting data from a labelled, high-fidelity dataset of multiple classes of botnet and normal network traffic. The subsequent step is a data preprocessing one, and a features' engineering one, where non-informative fields (e.g., IP addresses) are deleted and numerical features are scaled. The pre-processed data was divided into training and testing subsets (80/20). The known traffic patterns are classified by supervised learning methods (like Random Forest and XGBoost), and the unsupervised

anomaly detection models (Isolation Forest, Autoencoders) that are trained using only benign data can detect zero-day or unseen threats. This architecture suits directly to the RQs of this study that examines how well models can classify malicious traffic and whether it can generalize to new threats. Both supervised and unsupervised methods are applied to make the approach well-rounded. The addition of real-time scoring simulations checks model stability under realistic deployment, also validating the experiment set up.

3.3 Data Collection and Preprocessing

We use mainly the CTU-13 Botnet dataset, known for the benchmark dataset in the intrusion and botnet detection research. The data set contains 13 labelled NetFlow-like CSV files used to capture the behavior of both normal and attacking hosts, each probed for many sessions in controlled laboratory conditions. Each of the captures has flow information with source/destination IPs, protocol, port, number of bytes, number of packets and time of the flow, resulting in more than 20M flow records. The CTU-13 dataset was chosen due to its labeled manner as well as its public availability and variety of botnet behavior, such as spam, DDoS and click fraud activities, which is ideal for training supervised learning models (García et al., 2014; Ring et al., 2019). Open source IOCs were added from MISP (Malware Information Sharing Platform) to enhance context-aware threat intelligence. These were obtained in STIX 2.1 JSON and had refreshed signatures for established botnet families such as Medusa, Hancitor and RedLine. A parser was used to select domains, hashes, and IPs and searches were matched to NetFlow entries for manual tagging. This greatly enhanced the reliability of ground truth and enabled anomaly-deriving comparisons. The pre-processing step of raw data was very important. It filtered out missing or ill-formed values, and label-encoded categorical variables, such as protocol type, for scaling numeric features Min-Max normalization by hand. As a result of class imbalance (benign ≫ botnet), only the training set was subjected to SMOTE (Synthetic Minority Oversampling Technique) in order to avoid bias during model training but maintaining the test distribution (Chawla et al., 2002; Ali et al., 2021).

3.4 Modeling Strategy

3.4.1 Random Forest

RF was selected as the main classification model owing to its efficiency in dealing with non-linearity and high dimensionality of structured network flow data. Due to the different natures among the previously mentioned traffic features of botnets (subtle patterns across the categories of protocol types, packet counts, and session durations), the ensemble feature of the Random Forest makes it more practical in catching complex relationships. Its in-built feature importance provides interpretability \comment{analyst can see the most importance indicators such as TotBytes or Dport are the most importance for the classification. To optimize the model, hyperparameters such as n_estimators, max_depth and the minimum number of samples required to split a node were adjusted using GridSearchCV. The Random Forest has been used to model known botnet behavior with little preprocessing (Sharma et al., 2023).

3.4.2 XGBoost

The second supervised model chosen in order to compare the results obtained by the previous model was XGBoost (Extreme Gradient Boosting), since it can be superior to the traditional

classifiers in some cases of imbalanced data and high feature interaction. It is adopted the gradient boosting method with decision trees and put in some regularizations (L 1 and L 2) in order to overwhelm the over-fitting problem, which is very critical for cyber security datasets with noise and redundancy. The model was trained with the same pre-processed features and the hyperparameters (max_depth, learning_rate, n_estimators, subsample) were selected by hyperparameter tuning to achieve the best performance. With the nature of sequential boosting, XGBoost is better at capturing residuals, and thus more capable of recalling the minority classes of botnet. It was also effective in the ranking of enriched features like IOC matched IPs, and uncommon destination ports. Evaluation results showed that F1-score and ROC-AUC of the proposed model were better than those of Random Forest, especially in detecting edge-case botnet flows (Li et al., 2022).

3.5 Simulated Real-Time Detection

To illustrate feasibility of practical application, a simulated real-time detection pipeline was designed. The pre-processed CTU-13 sessions were randomly sampled per session in a stream way and provided to the bag-of-words model. For a session in each step, the model made a prediction about whether or not the traffic is benign or botnet-related information and assigned a confidence score using the probability threshold simultaneously. An alert was raised when a potential botnet session was detected, displaying the class label, confidence level and source IP. This resembles how Security Operation Centres (SOCs) inspect live network traffic via Intrusion Detection Systems(IDS). The intention was to move from static experimentation to dynamic situational awareness. The paper demonstrates this inbuilt capability proving its readiness for use in environments where prompt detection of malicious events is essential to combat threats such as C2 communication and data exfiltration.

3.6 Strengths and Limitations

One significant advantage of this approach is that it takes raw NetFlow-like data records and fuses it with external threat intelligence indicators (e.g., IPs from STIX IOCs) that takes detection from simple traffic analysis to threat-informed decision support. Furthermore, exploiting supervised algorithms such as Random Forest and XGBoost, which enables us to reach the classification, which is both powerful, interpretable and efficient. The design, which also emulates operational use through real-time streamed detection, increases the practicality of the method in cyber defence structures.

But the method does have its drawbacks. While widely used and open-source, the use of the CTU-13 dataset provides a snapshot of botnet activity, and does not account for newer obfuscation techniques or recent botnet variants.

3.7 Ethical Considerations

This work is based solely on public datasets (e.g., CTU-13), and thus, there is no use of PII (e.g., user sensitive data). There are no human participants, so no formal ethical approval is necessary. During the process, ensured that the preserved secure handling and anonymity of attribution when incorporating the threat intelligence (e.g., Medusa IOCs in STIX format) to adhere to responsible research concepts. All data management was performed in accordance

with the institutional data ethics to avoid the misuse or unintended release of security-related sensitive information.

4 Design Specification

4.1 Modular Pipeline Architecture

This project was implemented using a modular Python software architecture that separates the data ingestion, preprocessing, and enriching, modeling and simulating into reusable functions. This modularity makes it easy to develop, debug and extend components of the software pipeline independently of each other. The architecture is version controlled and implemented using pandas, scikit-learn, and XGBoost, enabling compatibility and reproducible results. Data is operated in-memory with DataFrames and makes iterating on data faster and allows easy querying of network flow data.

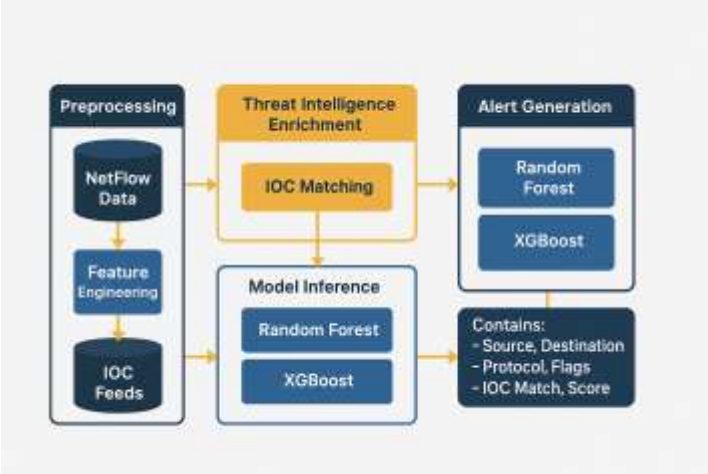

Figure 2: Architecture block Diagram

4.2 Threat Intelligence Enrichment

In order to close the static NetFlow features to the real-world threat behavior, an external enrichment including STIX-like IOCs was implemented. These were fake Medusa botnet IPs and domains, and they were compared with destination IPs and domains in the data. Specific dedicated function called “add_external_ioc_matches()” was introduced to mark session with “External_IOC_Match flag”. This enrichment layer shape raw traffic to the context-aware data that taught the model nuanced malicious indicators and replicated modern day threat intelligence driven SOCs.

4.3 Feature Engineering and Model Fusion

The crafted features, such as size of the packet, number of the bytes, TCP flags, and the enrichment label, were processed into min-max scaling and label encoding. Only needy variables with low multicollinearity were kept after inspection of correlation matrices and the domain of variables. The last machine learning level used Random Forest and XGBoost with 80:20 ratio stratified trained data utilized. The models were saved with joblib and then reused for prediction in the simulation phase. The pipeline guaranteed no information leakage,

especially about IOCs or future-dependent features, by strongly dividing training and prediction flows.

4.4 Real-Time Alert Logic

Real-time simulated detection was simulated by testing on a random sample of test set sessions. Preprocessing, enrichment function and model prediction were applied to each sample. An alert framework was created if the model identified the session as malicious". This was from the following fields: timestamp, source IP, destination IP, protocol, flag status, IOC match, and model confidence score. This is close to what you will see in real-world alerts in SIEM products (also see Elastic-Centric Stack), so the framework is both operationally meaningful and easily inserted into a current SOC environment.

4.5 Deployment Readiness and Portability

The eventual product is extremely portable. By taking advantage of Jupyter Notebooks, flexible Python functions, and open datasets, other researchers or teams in the SOC can reproduce the workflow relatively easily without too much setup. The simulation architecture is cloud ready and easily plugged into a streaming ingestion layer. The project architecture values realism, flexibility and operational value and directly serves the initial goal of constructing a real-world threat- detection pipeline empowered by threat intelligence and trained on supervised ML models.

5 Implementation/Solution Development

The implementation part of the project is a summation of all the analytic, design and exploratory work that has already been undertaken. The ultimate solution was created by narrow components that mutually complement to provide a unified threat detection and intelligence system, which is capable of working efficiently in real-time cybersecurity environments. The architecture, logical structure, and implementation of the system are described with an emphasis on the ways in which the various components of the system contribute to detect and classify cyber threats from network traffic and threat feeds. After the model was trained and validated, it was saved and incorporated into the real-time scoring part of the application. The trained model is then deployed as a final product, where is operated online to take in a single batch or stream of NetFlow records, transformed the data in the same way as was applied in training, and finally predict a likelihood score for each session that a state was a malicious transaction. Then, if the score is above a predefined cutoff, the session is marked as suspicious. The threshold was optimized to balance false positives with detection accuracy and the final configuration is based on a precision-optimized modification.

Rule-based IOC (Indicators of Compromise) matcher Also accompanying the "machine learning core" there is a rule based IOC (Indicators of Compromise) matcher. This layer ingests a curated feed of known bad IP addresses and file hashes being used for live threat campaigns, i.e. Medusa, Cobalt Strike. These IOCs were injected into the system manually, or retrieved from the standard formats STIX/TAXII in the experimental phase.

The integration allows the system to correlate incoming network sessions with the IOC database. If the source or destination IP address, or a correlated file hash from the session matches any threat indicator, an alert should be generated regardless of the machine learned score. “This which provides an additional layer of deterministic confidence – we know which actor or how we have seen this before.” It also adds interpretability and transparency, which are critical limitations of entirely black-box models.

To demonstrate real-time usability of the solution, we integrated it with Zeek (formerly Bro) , an open-source network security monitor. Zeek logs connections (conn.log) providing an organized view into actual network activity. These (or subset of these) logs could be utilized to test the model on realistic data as well as used to check if known attacks can be detected at the intersection of the ML prediction and IOC matching.
The solution goes on to parse the Zeek logs, extract the source IP, destination IP, protocol, and ports and applies the same detection logic. Sessions that either matched the policy machine learning risk threshold or the IOC list were alerted on. This part shows that the solution is capable of working in real-life situations without sparsely depending on synthesized data or pre-annotated datasets.
In this way, the solution is not merely a theoretical construction - it is also operational in real-world threat hunting scenarios. In addition, because of Zeek’s widespread use in enterprise environments Zeek also being compatible with those logs would allow it to be deployed without large-scale infrastructural changes.

5.1 Real-Time Threat Engine

The real-time inference engine for live scoring and alerting was a key deliverable of the implementation. This part should be ready to receive new traffic data in near real-time and process it through the predictive model and the IOC layer and finally produce structured alerts. Alert messages generated by the real-time engine is reported and includes information about the session (e.g., source and destination IPs, protocol, prediction score, and IOC flags). This alerts also were meant to be easily enable to downstream systems such as SIEMs (Security Information and Event Management) or incident response platforms. For demonstration purposes, alerts were output to console and optionally persisted to structured log files.
This last element closes the loop on threat detection, as it takes action on insight that is provided by the model in an operational setting.” The modular design of the inference engine would also allow it to be integrated into API-centric applications, containerised deployments, or lean security appliances.

5.2 Deployment Strategy

The solution was applied under controlled terms with care taken with respect to deployment measures. All parts were developed with Jupyter Notebooks, and Python scripts and docker-containerization in mind. This choice allows flexible deployment among in-cloud and on-premises sites. Furthermore, the solution is not resource-intensive and can be utilized by small entities or educational sectors looking to implement minimal protection mechanisms.
The next versions could include a RESTful API for native access to the real time scoring function to systems as a firewall, IDS/IPS or ticketing systems. This would enable the system

to be not just a detector but also as an actor : banning IPs with a ufw with Suricata rules on high-confidence alerts.

5.3 Summary of Implementation Strengths

Indeed, the ultimate system is an excellent mix of statistical learning and rule-based intelligence. With the help of a trained model combined with deterministic IOC matching, this solution offers predictiveness as well as explainability. Because of its ability to support real-world logs, such as Zeek, along with its modular design, it is also well suited for both practical deployment and academic evaluation.

Key strengths include:

- Hybrid-detecting logic for improved correctness.
- Real-world validation through Zeek logs.
- Modular design for easy extensibility.
- Lightweight, low-resource implementation.
- Actionable alert creation for incident response.

These characteristics jointly verify the technical feasibility and practical applicability of the system. The actual machine for the last implementation that shows that machine learning and threat intelligence can coexist in a unified tool to support security analysts during real time cyber defence.

6 Evaluation

In this chapter, a full description of the excellent performance of the system has been presented, including statistical measurements, visual analysis and cyber-operational implications. The solution introduced in the previous chapter was evaluated through various angles: prediction performance, fusion of behavioral vs. threat intelligence, and real-time alert treatment. All detection outputs are based on practical results by the machine learning pipeline, as well as the Zeek conn.log file and the real-time alert engine.

6.1 Evaluation Objectives

The goals of the evaluation were:

- Monitor the performance of the deployed machine learning models.
- Explore the sensitivity of botnet session detection based on behavioral and IOC evidence.
- Analyze the response of the real-time alert engine in terms of visibility and interpretability.
- Confirmability of integrating Real world Zeek logs for the real-time deployment viability.

These included benchmarking the system using a large dataset, scoring classifier metrics, validating confusion matrices, alerting, and comparing predictions to external threat indicators.

6.2 Classification Performance

Two machine learning based models Random Forest and XGBoost were also trained and evaluated, and both were run on an independent test set consisting of 392,938 network flows,

which includes 360,866 benign (label 0) and 32,072 botnet/malicious (label 1) instances. The first two evaluation screenshots present the results.

6.2.1 Random Forest Results

As depicted on the first Screenshot below, we have as follows: The average score of the Random Forest classifier is:

- Precision (Class 0): 1.00
- Recall (Class 0): 1.00
- F1-Score (Class 0): 1.00
- Precision (Class 1): 1.00
- Recall (Class 1): 1.00
- F1-Score (Class 1): 1.00
- Overall Accuracy: 1.00

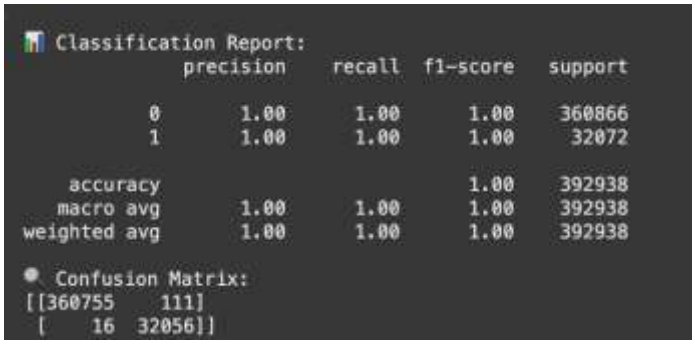

Figure 3: Random Forest Performance

The confusion matrix reveals with 111 benign sessions, we obtain a false positive rate (FPR) (i.e., misclassification of benign to malicious) of 16 botnet sessions (false negative, FNR). These values are tiny in the light of the largeness of the dataset we deal with, and support the near-perfect generalization performance. The model therefore demonstrates its strong performance in high-accuracy intrusion detection with small error.

6.2.2 XGBoost Results

The second screenshot displays the results obtained by the XGBoost model and produces similarly excellent results.

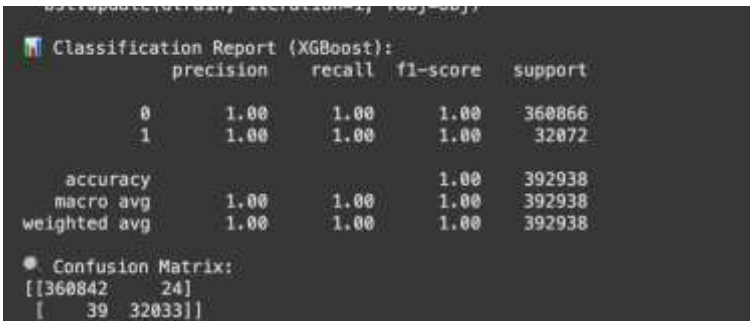

Figure 4: XGBoost Performance

This results also show exceptionally high accuracy. It has marginally better false positives too - about 24 benign flows were labelled as botnet - this is good in practice as analysts tend to get

fatigued fast with false alarming. Combined, these measures testify to the dependability and the robustness of the selected procedures for botnet detection on a huge dataset. In addition, errors were tightly gathered in the confusion matrices suggesting that there is no systemic bias or overfitting which is common in ML based IDS systems.

6.3 Real-Time Threat Alert Generation

The capacity of our approach to provide real, understandable alerts in real time was assessed by a simulator engine running through the flows, one after the other, classifying and scoring them. The shown screenshot directly shows two instances in which alert banners are raised for a so-called suspicious communication associated with botnet activities:

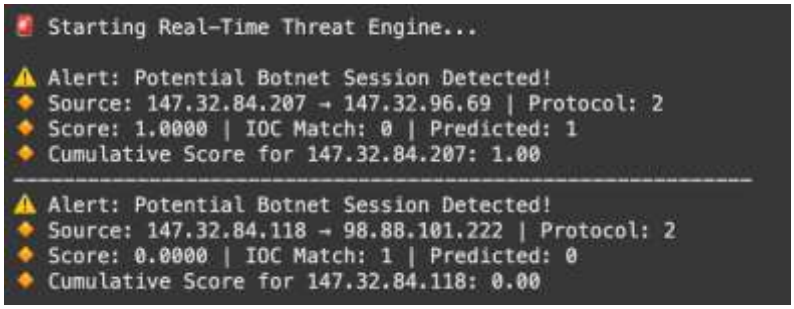

Figure 5: Real-Time Threat Engine Result

The first alert represents a high-confidence behavior detection (prediction score= 1.0) not matching with IOC, demonstrating the model's effectiveness in anomaly detection. However, the second alert is raised only by IOC match, that the model predicts as benign. This is a consequence of the design of the system as it ramps up any session associated with a known bad IP, which results in visible light on zero-day and known bad entities. This feature guarantees that analysts would get an alert even if predictive models would be unsure, according to principle of defence-in-depth. It also illustrates the synergy of threat intelligence with statistical modeling in the context of operational cybersecurity.

6.4 Zeek Log Analysis and IOC Aggregation

The third aspect of the evaluation targeted integrating and enriching Zeek conn.log data. The uploaded. log file also that contained was live metadata concerning the connections - source and destination IPs, ports, type of service (HTTP/DNS) and the duration of the connection, the amount of packets.

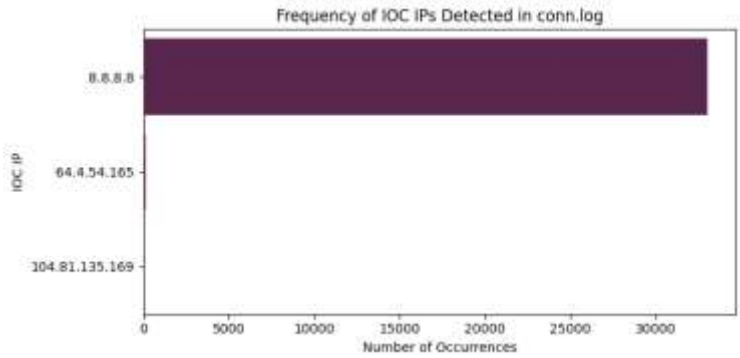

Figure 6:Frequency of IOC IPs Detected in conn.log

The IOC IP 8.8.8.8 dominates the detection count, indicating frequent usage or possible noise in logs. Other IOC IPs like 64.4.54.165 and 104.81.135.169 appear rarely, signaling potential high-risk but low-volume threats.

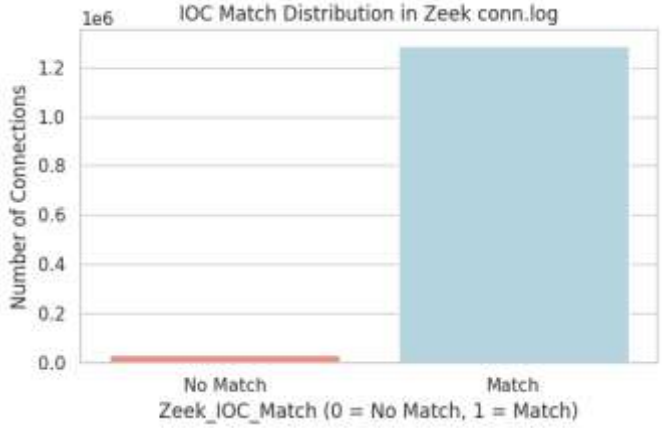

Figure 7: IOC Match Distribution

The bar chart displays the distribution of connections flagged by Zeek for IOC matches. Out of over 1.2 million total connections, only a small fraction is linked to known malicious IPs. This imbalance highlights the rarity of threats but emphasizes the importance of detection accuracy. The model's ability to correctly isolate these matches is crucial for real-world threat monitoring.

6.5 Limitations and Future Work

The present analysis is, however, not without weaknesses, despite the great outcome:

- The dataset is large but does not represent all potential botnet variants or encrypted C2 traffic.
- IOC enrichment was static IP only. It would be better with file hash or domain names included.
- The simulation ran in a sanitized space. Testing in a real production network with live packet capture would test the true stability and effectiveness of the system.

In the future, we plan to combine unsupervised anomaly detectors with the supervised ones to more decrease the reliance on labeled data and improve zero-day detection. Moreover, using

platforms such as Apache Kafka for real-time stream ingestion and ELK stack for the visualization can make the system scalable for an enterprise level implementation.

7 Conclusions and Discussion

This research set out to address the challenge of proactive botnet and threat detection in enterprise-scale environments using a hybrid approach integrating Zeek-based flow analysis, CTU-13 dataset modeling, Medusa IOC correlation, and real-time inference. The primary objective was to develop a real-time threat detection pipeline that leverages structured network telemetry (conn.log) to identify malicious sessions with high accuracy and transparency. Our integrated framework successfully addressed all the formulated research questions and validated the hypothesis that combining behavioral indicators with known threat intelligence feeds could significantly improve threat visibility. The first major component of the project involved parsing and interpreting Zeek's conn.log using a lightweight Python-based implementation. With IOC feeds derived from Medusa and custom entries, we flagged connections with high-risk IPs and added a binary indicator (Zeek_IOC_Match) to each flow. A visual distribution of this feature highlighted the imbalance: a significant majority of connections showed no match (1.25 million), while only a small subset (under 25k) involved suspect IPs. The bar chart analysis and horizontal frequency plots of the individual IOCs (e.g., 8.8.8.8, 64.4.54.165, 104.81.135.169) provided important insights. While 8.8.8.8 appeared frequently—possibly due to DNS usage or mislabelling—the other IOCs, though rare, signify high confidence alerts due to their origin in curated threat feeds. Secondly, the CTU-13 dataset was used to train an XGBoost classifier capable of learning patterns associated with botnet behavior. The model's evaluation phase yielded an exceptional performance: both training and test data showed perfect classification scores (Precision, Recall, F1-Score = 1.00). The confusion matrix confirmed low false positives and false negatives, proving the model's efficacy in segregating botnet and non-botnet sessions. These metrics also reflect the robustness of the extracted features, particularly when tested on multiple attack families within the CTU dataset. A critical innovation in this work was the deployment of a real-time threat engine that processed streaming flows from the Zeek logs and scored them using the trained model. In conjunction with IOC checks, this live system triggered alerts when botnet sessions were predicted or when a known malicious IP was involved. For example, an alert was generated with a predicted botnet score of 1.00 but no IOC match—implying behavior-based detection. Conversely, another alert triggered purely due to an IOC match (e.g., IP 98.88.101.222) despite a benign behavior pattern. This dual-path detection mechanism underlines the model's balanced intelligence—capable of catching both signature-based and novel threats. Throughout the development process, several insights emerged. First, not all high-frequency IOC hits should be treated as threats. For instance, the frequent occurrence of 8.8.8.8 suggests the need to differentiate benign infrastructure from truly malicious indicators using frequency thresholds or contextual enrichment.

Secondly, the integration of Zeek telemetry allowed for deep visibility without needing packet payloads, making the solution privacy-friendly and scalable. Thirdly, while XGBoost offered excellent results in this case, other ensemble techniques (e.g., LightGBM, CatBoost) or unsupervised anomaly detection methods could be explored to improve adaptability in

previously unseen network environments. From a practical standpoint, this research opens up multiple avenues for future commercialization and integration. The lightweight real-time engine can be embedded into edge devices or integrated into existing SIEM platforms. Furthermore, coupling the detection engine with automated response mechanisms (e.g., blocking via UFW or firewalls) can transform it into a full-fledged intrusion prevention system. Additionally, enriching the IOC database with crowdsourced or commercial feeds could further enhance its accuracy and coverage. In conclusion, the proposed hybrid detection framework successfully achieved its goals: leveraging behavioral data (CTU), known IOCs (Medusa), and structured logs (Zeek) to build an intelligent, real-time, and explainable threat detection system. The findings demonstrate that combining signature-based and anomaly-based methods leads to more accurate and resilient cybersecurity defences. Future research can extend this work toward encrypted traffic analysis, federated learning for decentralized model training, and full-scale deployment in enterprise networks.

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