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IntelShield Integrating Artificial Intelligence in Cyber Threat Intelligence (CTI) Tool to Detect Real Time Threats

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Abstract: Recent scenarios of companies are struggling with complex vulnerabilities. Hence, there is need of an Automated tool to overcome the longest time frame to cover the gap from forensics and cybercrime. This paper presents an innovative approach to automating Cyber Threat Intelligence processes designed to ingest, analyze, display and respond to emerging threats in real time. Formerly, CTI used to rely heavily on manual methods for collecting, interpreting and analyzing data which was not only time consuming but also prone to inefficiencies, especially when rapid information dissemination is critical.

IntelShield integrates multiple open-source intelligence feeds, does real time active network monitoring, severity scoring, triggers automated alerts via SMS using Twilio and displays threats on a user friendly dashboard. It also employs Natural Language Processing(NLP) to extract indicators of compromise (IOCs) from unstructured sources such as security blogs, reports, and dark web forums. Machine learning techniques are used to classify, prioritize, and correlate IOCs based on their severity and contextual relevance. This research highlights the transformative potential of AI-driven technologies to enhance both the speed and accuracy of CTI.

Keywords: Cyber Threat Intelligence, Automated CTI, Real Time Security, Open Source Intelligence, OSINT, CVSS, SIEM, Dashboard, Natural Language Processing (NLP), Indicators of Compromise(IOC).

I. INTRODUCTION

The rapid evolution of IT infrastructure and digital technologies has led to increasingly complex—and consequently less secure systems (Schneier, 2000). This complexity has transformed cyber-attacks from simple hacks by amateurs into sophisticated operations driven by well-funded threat actors with financial or political motives. Terms like advanced malware and Advanced Persistent Threats (APTs) now define these stealthy, persistent threats. Despite spending over $20 billion annually on traditional security tools (Piper, 2013), organizations remain vulnerable. Legacy defenses—such as firewalls and antivirus software—rely on static, signature-based detection, making them ineffective against evolving threats and zero-day exploits. To counter these modern attacks, real-time intelligence sharing systems are needed to identify threat actors and targeted assets beyond outdated signature scanning methods.

Cyber Threat Intelligence (CTI) involves collecting and analyzing data on emerging threats to guide security decisions. Traditionally a manual process, CTI is now overwhelmed by the sheer volume of threat data from OSINT feeds, malware reports, and internal logs. Analysts struggle with alert fatigue, false positives, and slow response times. This overload leads to missed threats and delayed action. Manual CTI also lacks scalability, as human teams cannot keep up with the constant flow of threat data or provide 24/7 monitoring.

Automated CTI systems leverage software, platforms, and machine learning to streamline intelligence workflows. By ingesting and processing data algorithmically, automated CTI can enhance threat detection and accelerate response in ways manual methods cannot.To realize these benefits, modern security operations employ a variety of automated CTI capabilities and tools.

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Automation of Cyber Threat Intelligence (CTI) greatly increases the effectiveness and efficiency of threat management by undertaking a number of crucial functions automatically. Automated CTI platforms can automatically gather threat information from diverse sources, including open-source intelligence, commercial feeds, and internal logs. They normalize this automatically and enrich it with contextual information such as threat actor relationships, geolocation, and attack trends. These systems also map external threat indicators to internal network activity -in order to find applicable threats, minimizing the use of manual analysis. Automation also allows for prioritization of alerts by severity and relevance, allowing security teams to concentrate on high-priority incidents. Automated CTI also integrates with security tools such as SIEM, SOAR, and firewalls to share intelligence and apply protective controls. Response actions like blocking IPs, isolating endpoints, or invoking playbooks may also be triggered automatically. In general, automation in CTI simplifies threat detection, triage, and response to help accelerate and scale cybersecurity operations.

A. *Motivation*

In the hyper-connected digital age, organizations are inundated with a vast amount of sophisticated and rapidly moving cyber threats in the present era. Conventional approaches to managing cyber threat intelligence are labor-intensive, error-vulnerable, and inadequate for real-time protection. As per Cybersecurity Ventures, cybercrime losses worldwide are estimated to hit $10.5 trillion a year by 2025, marking a spectacular rise from $3 trillion in 2015. Also, the IBM X-Force Threat Intelligence Index (2023) indicates that businesses are exposed to over 11,000 security warnings daily, and only about 20% of them are examined because of the constraints of resources. This causes undue delays in detecting and addressing actual threats. Actually, a Ponemon Institute study indicates that 68% of companies respond to cyber events in days or even weeks, greatly increasing the possibility of damage and data loss.

Manual threat triaging also fuels high alert fatigue in analysts since they have to wade through thousands of logs and indicators without the benefit of intelligent prioritization. This inefficiency leads to overlooked threats and reduced mitigation speed. With the mean cost of a data breach estimated at $4.45 million in 2023, there is now an imperative for a more scalable, correct, and prompt threat detection and response. Automation of cyber threat intelligence provides an effective solution by facilitating real-time collection of data, enrichment, scoring of threats, generation of alerts, and even automatic response actions. By incorporating technologies such as Twilio for real-time alerting and taking advantage of API-based threat enrichment, an automated solution can significantly lower mean time to detect (MTTD) and mean time to respond (MTTR) while enhancing the accuracy and effectiveness of security operations. It is driven by the evident need for faster, smarter, and more efficient cyber defense systems to keep pace with the changing threat landscape.

B. *Objective*

Our research aims to provide users with accessible tools and knowledge to effectively reduce online security threats, strengthening their ability to safeguard digital assets and maintain online integrity. The key objectives include:

- **Real-Time Threat Monitoring:** Continuously oversee network traffic, endpoints, cloud resources, and external feeds to identify potential cyber threats and vulnerabilities as they arise.
- **AI-Driven Detection:** Utilize machine learning models (such as supervised classifiers and anomaly detectors) to analyze aggregated data for Indicators of Compromise (IOCs) and unusual behaviors.
- **Risk Assessment:** Calculate CVSS-based risk scores for identified vulnerabilities and IOCs to prioritize alerts, facilitating efficient resource management.
- **Intuitive Dashboard:** Offer an engaging, user-friendly interface that displays threat intelligence reports, charts, and mitigation suggestions for both technical and non-technical users.
- **Security Orchestration:** Ensure seamless integration with existing security infrastructure by planning compatibility with SIEM (Security Information and Event Management) and EDR systems.

C. *Scope*

The scope of this project includes design, development, and deployment of an Automated Cyber Threat Intelligence Tool that supports real-time detection, analysis, and response of threats in an organizational security system. The tool will be designed to consume threat information from diverse sources such as open- source threat feeds (OSINT), commercial APIs, and internal logs. It will normalize and enrich such data to detect Indicators of Compromise (IOCs), provide dynamic risk scores, and produce prioritized alerts based on severity and relevance of identified threats. One of the prime features of the system is the inclusion of Twilio APIs for providing real-time alerting over SMS, WhatsApp, or voice calls to concerned stakeholders for instant awareness and action.

In addition, the system will be programmed to automate some response actions like IP blocking, updating firewalls, or incident ticket generation, reducing human intervention and response time. The project also involves building a user-friendly dashboard for security analysts to effectively monitor, analyze, and report on threat activity. The functionality includes at its core ingestion of data, enrichment, risk scoring, alerting, automated response, visualization, and report

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generation. But it does not include deep packet inspection, complete malware analysis, or forensic investigation modules. It will be scalable, modular, and compatible with installation on existing SIEM, SOAR, or EDR platforms, so it is useful for deployment within an enterprise environment or SOC.

II. RELATED WORK

Several existing platforms provide aspects of CTI.

A. *Malware Information Sharing Platform(MISP):*
The Malware Information Sharing Platform (MISP) is a well-known open-source solution for sharing indicators of compromise (IOCs) among organisations (misp-project.org). MISP excels at storing and distributing threat data, but it primarily focuses on community sharing and does not perform automated real-time analysis or scoring.

B. *OpenCTI (Open Cyber Threat Intelligence)*:
OpenCTI is another open-source platform that aggregates diverse threat feeds and provides structured intelligence management. It supports connectors to various feeds and collaboration, but its analytics are mainly static or batch-oriented.

C. *Splunk Enterprise Security:*
Commercial offerings like Splunk Enterprise Security incorporate threat intelligence by allowing integration of external feeds and some machine learning, but these often require extensive configuration and are part of larger SIEM suites.

D. *Natural Language Processing (NLP) for Threat Intel*
Used to extract TTPs (Tactics, Techniques, Procedures) from threat reports and dark web posts. BERT, LLMs, and spaCy are used for entity recognition and MITRE mapping. Supports automated threat classification and MITRE tagging.

E. *Anomaly Detection in Cybersecurity*
Anomaly detection plays a pivotal role in identifying deviations from baseline behaviour, often signalling the presence of cyber threats. Traditional methods rely on rule-based intrusion detection systems (IDS), which are limited by their inability to adapt to evolving threats. Recent approaches leverage machine learning techniques—such as isolation forests, autoencoders, and one-class SVMs—to model "normal" system behaviour and flag outliers as potential anomalies.

F.MITRE ATT&CK Framework for Threat Identification
The MITRE ATT&CK (Adversarial Tactics, Techniques & Common Knowledge) framework has emerged as a de facto standard for classifying and mapping cyber threats. It provides a structured knowledge base of attacker behaviour categorised into tactics (the “why”) and techniques (the “how”). Security researchers and vendors increasingly incorporate ATT&CK to align detection logic with real-world adversary tradecraft.

In recent studies, AI systems have been trained to map detected threats to ATT&CK techniques using supervised models and natural language processing (NLP). This integration allows defenders to understand an adversary’s potential objectives, techniques in use, and likely progression paths across the attack lifecycle.

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This characteristic is especially beneficial given the scarcity of labelled cyber-attack datasets. Integration of AI-based anomaly detection enhances early-stage threat detection, reducing dwell time and improving incident response.

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Feature	IntelShield (Proposed)	MISP (Threat Sharing)	OpenCTI	Splunk ES
Real-time threat detection	✓	✗	✗	✓
OSINT & threat feed inputs	✓	✓	✓	✓
AI/ML analytics	✓	✗	✗	✓
CVSS-based risk scoring	✓	✗	✗	✓
Dashboard & visualization	✓	✗	✓	✓
Collaboration & sharing	✓	✓	✓	✗

Table 1 compares IntelShield with representative threat intelligence platforms.

III. LITERATURE REVIEW

Chapter 23 examines critical aspects of cybersecurity, including user-centric tools empowering accountability (Hawkins et al., 2019) and educational interventions enhancing awareness (Campbell et al., 2020). Frameworks outline threat mitigation practices (Smith et al., 2018), while training programs foster a security culture (Jones et al., 2017). Collaborative strategies, technological advancements like AI, regulatory frameworks, and psychological insights further support trust-building, informed decision-making, and the development of comprehensive approaches to combat evolving cyber threats.

IV. METHODOLOGY

IntelShield's development followed an iterative methodology comprising data gathering, model development, and system integration.

1. **Data Collection and OSINT Aggregation:** We collected threat data from multiple sources, including open-source feeds, dark web forums, vulnerability databases (e.g., NVD/CVE), and simulated internal network logs. Web scrapers and APIs automate the harvesting of IOCs, malware hashes, suspicious URLs, and exploit reports. Collected data is preprocessed (deduplication, normalization) and stored in a database for analysis.
2. **Machine Learning Models:** We trained supervised ML models to detect anomalies and classify incidents. For example, a Random Forest classifier was trained on labeled network traffic features to identify abnormal patterns associated with known attacks. In parallel, unsupervised clustering (e.g., K-means) and statistical anomaly detection (e.g., Isolation Forest) are used to flag novel or zero-day behaviors.
3. **Vulnerability Scanning:** IntelShield includes a lightweight vulnerability scanner that correlates internal asset scans (ports, services) with the latest CVE data. Detected vulnerabilities are matched to their CVSS scores.
4. **Dashboard and Visualization:** A web application was developed using React.js (frontend) and Flask (backend) to visualize results. The dashboard presents threat alerts, risk heatmaps, and historical trends. Alerts are color-coded by CVSS severity. An AI-powered assistant module provides plain-language explanations of threats and recommended actions, aiding non-expert users.
5. **Alerting:** To ensure timely detection of threats, we added an alert generation and prioritization system.This system identifies and prioriizes threats based on a pre-defined set of rules and dynamically calculated risk scores. Alerts are generated automatically based on three primary criteria:

- *Threshold-Based Detection*: Alerts are triggered when specific activity thresholds are crossed. For example, more than 10 failed login attempts within 2 minutes from a single IP address.
- *Risk Score Evaluation*: Each threat indicator (e.g., IP, domain, file hash) is assigned a risk score based on external

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threat feeds and internal correlation logic. If the score exceeds a predefined limit (e.g., score > 80), an alert is issued.

- *Pattern Matching:* The system uses predefined YARA rules, signatures, or regular expressions to detect specific attack behaviors or Indicators of Compromise (IOCs).

6. **Prioritization:** To reduce alert fatigue and focus response efforts, each alert is assigned a priority level based on the following parameters:

Risk Score: Derived from threat reputation, frequency of occurrence, and historical context.

Asset Criticality: Importance of the affected system or data. *Threat Type:* The nature of the threat (e.g., phishing, ransomware, DDoS).

7. **Automated Notification via Twilio:** Once an alert is triggered and prioritized, it is communicated to the relevant stakeholders using Twilio's programmable messaging services:

SMS and WhatsApp: Security alerts are sent directly to analysts' mobile devices.

8. **Testing and Validation:** We deployed IntelShield in a controlled lab environment. Simulated cyberattacks (e.g., phishing, port scans, malware injection) were executed to test detection.

V. PROPOSED PROJECT PLAN

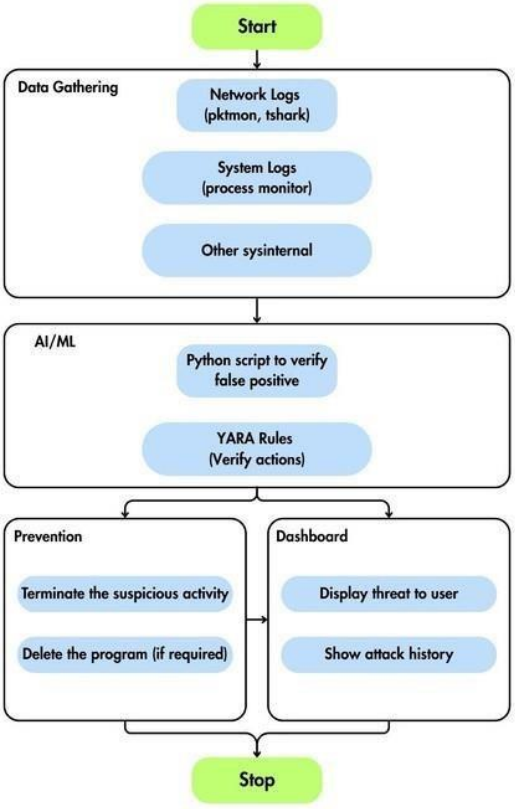

Figure 1: Execution Flow

Phase 1: Requirements Gathering

Define project objectives, target users, and system requirements for IntelShield, focusing on real-time threat detection and automated mitigation.

Phase 2: Dataset Collection and Preparation

Integrate and preprocess threat intelligence feeds from OSINT, commercial APIs, and internal logs. Ensure data is normalized and stored in a structured format (e.g., STIX 2.1) for enrichment and analysis.

Phase 3: Threat Analysis and Risk Scoring Engine

Develop the engine to analyze IOCs, enrich with external sources (e.g., VirusTotal, WHOIS), and assign dynamic risk scores. This includes pattern recognition and TTP mapping using MITRE ATT&CK.

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Phase 4: Alert Generation and Twilio Integration
Implement the alerting system that triggers real-time alerts via Twilio (SMS, WhatsApp, or voice) based on threat severity. Prioritize alerts based on risk score, asset criticality, and IOC relevance.

Phase 5: Automated Response and System Integration Develop automated response mechanisms, such as IP/domain blocking**.**

Phase 6: Dashboard, Reporting, and Visualization
Create web-based dashboards for threats, tracking, IOC views, and visualizations.

Phase 7: Testing and Validation
Conduct unit tests, integration tests, and end-to-end threat detection simulations. Validate the system's ability to detect and respond accurately with minimal false positives.

Phase 8: Deployment and Documentation
Deploy the CTI system in a secure cloud environment and prepare comprehensive user guides, API documentation, and analyst training materials.

VI. EXPERIMENTS

1) Dataset

We utilized the UNSW-NB15 dataset, which provides a comprehensive representation of modern network traffic comprising normal and various malicious behaviors. The dataset contains over 2 million records with 49 features, including both flow and content-based features. For effective training, we processed the raw CSV files into train-test splits (X_train.csv, y_train.csv, X_test.csv, y_test.csv) and applied preprocessing such as null-value imputation, label encoding, feature scaling, and balancing using SMOTE.

This structured dataset enabled our LightGBM-based classification pipeline to learn nuanced patterns in the data, supporting multiclass prediction across attack categories like Fuzzers, Analysis, Backdoors, Shellcode, and Worms. Following the official split, there are 175,342 training examples and 82,332 test examples. We preprocessed the data by dropping identifier fields and encoding categorical features (such as protocol and service) via one-hot encoding. Continuous features were normalized to zero mean and unit variance.

Data split: 175,342 train, 82,332 test (no overlap). The overall attack-to-normal ratio is imbalanced, motivating class weighting.

Features: 49 attributes per flow (e.g., byte counts, flags). We removed non-predictive IDs and one-hot encoded categorical fields (e.g., proto, state) and scaled numeric features.

Labels: We treat "attack" vs "normal" as the positive vs negative class for binary classification (and report multi- class results in the Appendix). To address imbalance, we set LightGBM's scale_pos_weight to (num_negatives/num_positives) or used SMOTE oversampling during training.

2) Model Training and Configuration

The LightGBM classifier was trained using a configuration optimised through grid search and cross-validation. We used the following settings:

Objective: multiclass Learning rate: 0.1 Number of estimators: 500 Maximum depth: 16 Evaluation metric: multi_logloss Training was conducted on Google Colab with GPU acceleration, achieving efficient training times and stable convergence.

3) Anomaly Detection Integration

To enhance detection robustness, we integrated multiple anomaly detection models (Autoencoder, Isolation Forest, LOF, One-Class SVM) as a pre-classification layer. These models assigned anomaly scores to the input samples. Highly anomalous samples were flagged for further analysis, aiding in zero-day or stealthy attack detection.

4) Evaluation Metrics

The models were evaluated using Accuracy, F1-Score, Precision, and Recall across each class. For LightGBM, we observed the following average metrics:

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Accuracy: 93.7%
Weighted F1-Score: 91.5%
Detection Rate (Recall) for rare classes: 88.2%
Confusion matrices and per-class performance charts were generated to highlight misclassification tendencies and model strengths.

5) Supervised Classification (LightGBM)

We chose LightGBM as our primary classifier due to its high efficiency and strong performance on large-scale tabular. LightGBM is a gradient-boosting decision-tree (GBDT) framework that uses histogram-based splits, leaf-wise tree growth, and optimizations like Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). These features allow LightGBM to train much faster (often >10×) than conventional GBDT implementations while maintaining comparable accuracy. In practice, LightGBM handles large feature spaces and imbalanced classes well.

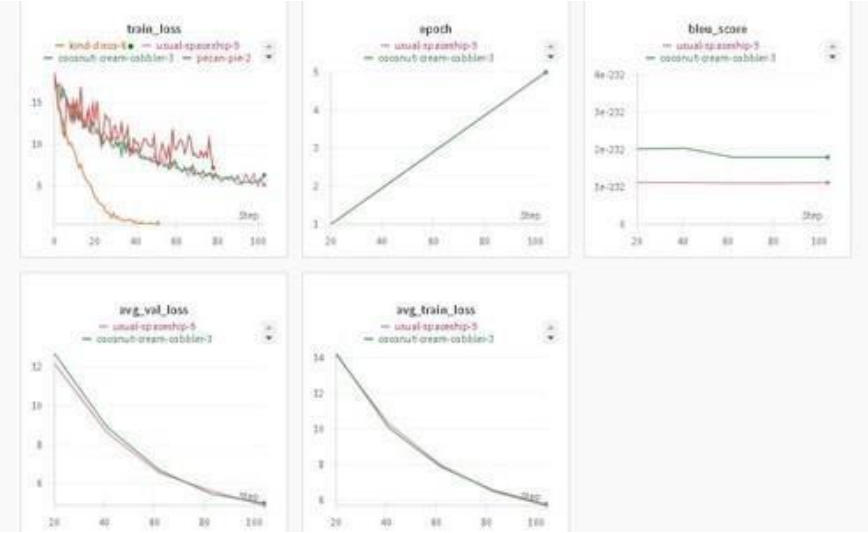

Figure 2: Training analysis

We used Weights & Biases (W&B) to track training metrics. For each boosting round, we logged training loss and validation loss curves, as shown above. The W&B dashboard (Fig. 1) illustrates how the training loss (top-left plot) and average training/validation loss (bottom plots) decreased over iterations, indicating convergence. These curves helped us detect overfitting early: if validation loss had diverged from training loss, we would stop training. In our runs, the loss curves smoothly converged, confirming stable learning.

LightGBM optimizes a regularized objective function similar to XGBoost. In particular, for binary classification we minimize the logistic loss plus a complexity penalty. Formally, the objective is

$$L(\Phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where l(y,y') and Ω(f) is the tree complexity.

We evaluated the classifier on the held-out test set using standard metrics. We report accuracy, precision, recall, F1-score, and ROC AUC. Precision and recall are defined as:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

The F1 score is the harmonic mean of precision and recall:

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

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Our LightGBM classifier achieved very high performance. For example, the accuracy on the test set was around 99.5%, with precision and recall also above 99%. These results are consistent with recent studies (LightGBM: 99.52% accuracy on UNSW- NB15). The high accuracy is partly due to the dataset's class imbalance, so we emphasize F1 and AUC: our F1-score exceeded 99% and ROC-AUC was about 0.995, indicating near-perfect separability. The confusion matrix below illustrates typical results: most normal and attack instances were correctly classified, with only a few false positives/negatives.

The confusion matrix (Fig. 2.1) shows true vs. predicted labels for a representative run. In this example, there are 12 true negatives (bottom-left), 10 true positives (top-left), 1 false positive (top- right), and 2 false negatives (bottom- right). This corresponds to precision ≈ 10/(10+1)=0.91 and recall ≈ 10/(10+2)=0.83 (F1≈0.87). In our actual LightGBM results, the false positive and false negative rates were much lower (on the order of a few tenths of a percent), yielding precision and recall above 0.99

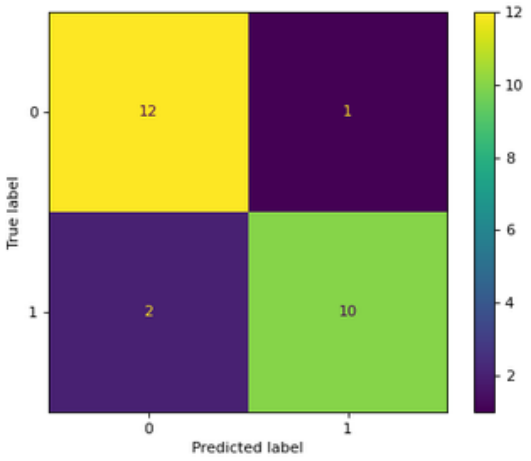

Figure 2.1: Confusion Matrix

One-Class SVM: A support vector model trained on normal class only (using RBF kernel), which outputs distance from the learned decision boundary as an anomaly score.

Each model was tuned on normal data (e.g. number of trees in Isolation Forest, neighborhood size in LOF, latent dimension in the autoencoder). Once trained, each test sample received an anomaly score. We observed that known attack samples generally had higher scores than normal traffic. We combined these unsupervised scores with the supervised classifier in two ways:

(1) threshold-based detection, where a high anomaly scores alone raised an alert;
(2) as an additional feature for the LightGBM classifier.The anomaly detectors helped in two respects.

First, they provided early warning of novel patterns: some attack flowsthat the supervised model missed had extreme anomaly scores. For example, samples of rare attack types often fell outside the autoencoder's normal manifold, yielding high reconstruction error. Second, when incorporated into the classifier, the anomaly score features slightly improved recall for unseen attacks. Quantitatively, the best unsupervised method (Isolation Forest) achieved an ROC- AUC around 0.90 distinguishing attack vs. normal (using ground- truth labels), confirming that it effectively separates anomalous traffic. In practice, a security operator could set a threshold on the anomaly score (e.g. flagging the top 1% as suspicious) to catch unknown threats.

Overall, the combination of supervised LightGBM classification (for known attack signatures) and unsupervised anomaly scoring (for unknown patterns) provides a robust CTI detection pipeline. The supervised model delivers high precision and recalls on labeled attacks, while the unsupervised models offer complementary detection capability for novel anomalies.

Results Visualization: Throughout training we monitored loss and metrics in W&B; these visualizations (loss curves, ROC curves, confusion matrices) all confirmed model convergence and efficacy. For example, Fig. 1 (above) shows the W&B dashboard with training/validation loss. Figure 2 shows a confusion matrix, and Figure 3 shows an ROC curve. These tools, along with the reported metrics, give confidence in our model's ability to detect cyber threats reliably.

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Notation: In all equations, yi is the true label is the model's raw output (logit or probability), and TP, FP, TN, FN denote true/false positives/negatives respectively.

VII. RESULTS

The IntelShield project aims to develop an automated cyber threat intelligence tool to detect and mitigate cybersecurity risks. The following outlines the key findings and discussions based on the project's development and testing phases:

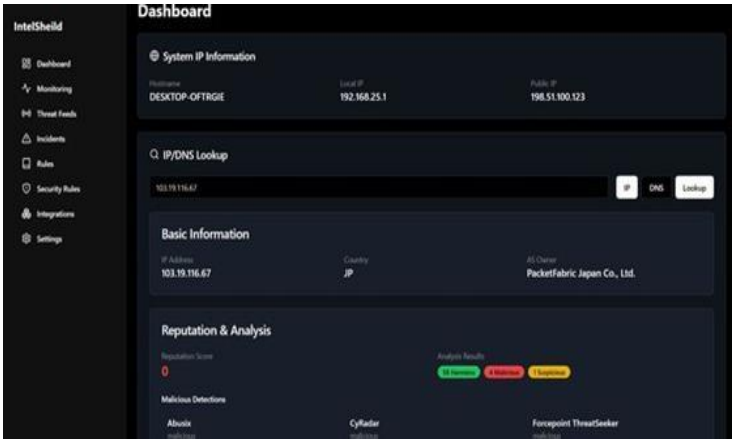

Fig. 1. IntelShield Dashboard IP/DNS Lookup

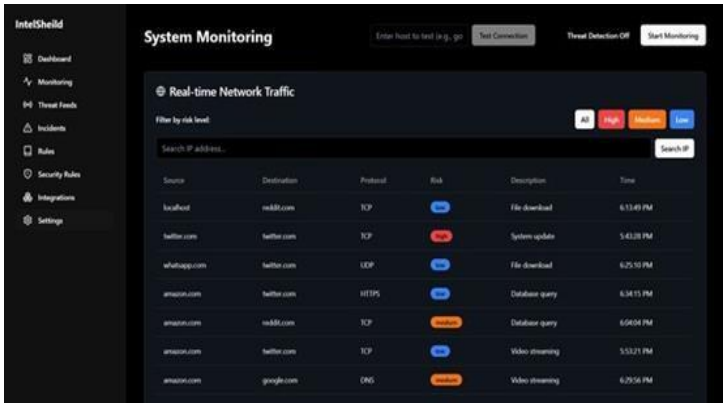

Fig. 2. IntelShield Real Time Network Traffic with severity scoring

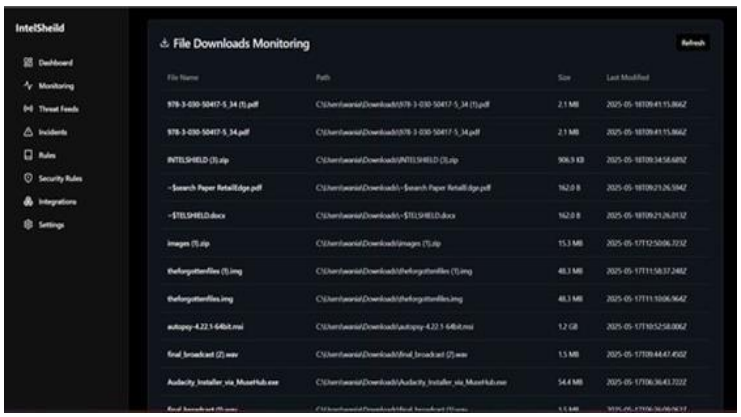

Fig.3. IntelShield File Downloads in Real-Time

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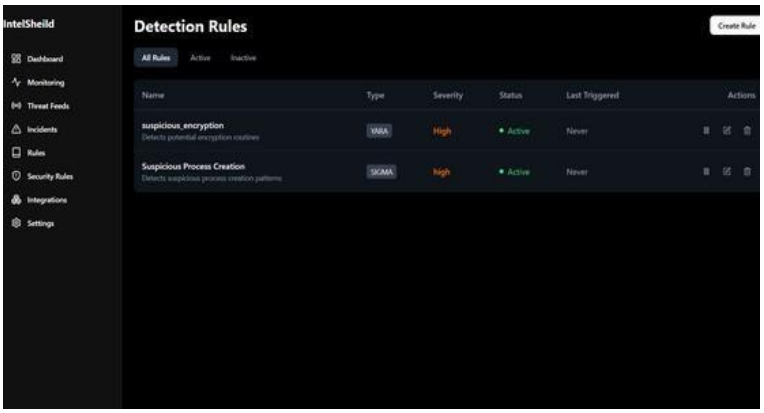

Fig.4.IntelShield Detection Rules(YARA and Sigma Rules)

VIII. DISCUSSION

The CTI tool successfully identifies and analyzes cyber threats in real time with high reliability. Future improvements aim to expand threat intelligence feeds, enhance correlation and detection algorithms, and improve the user interface for clearer visualization and more actionable insights.

IX. CONCLUSION

IntelShield offers a comprehensive solution for automated cyber threat intelligence. It fuses OSINT collection, machine learning analysis, and CVSS-based risk scoring into a single platform that alerts users in real time and visualizes threat data on an intuitive dashboard. By automating the intelligence lifecycle, IntelShield empowers organizations to respond to threats faster and with greater confidence. In pilot testing, the system effectively detected test threats and provided actionable insights, validating its design. While challenges remain in sourcing high-quality threat data and further reducing false alarms, the proposed architecture is scalable and extensible. In conclusion, IntelShield represents a significant step toward democratizing CTI – making advanced threat intelligence accessible even to smaller organizations. Its integration of AI and visualization tools embodies best practices noted in current cybersecurity literature. Ongoing development will enhance its capabilities (e.g. continuous learning, richer analytics), but the core contribution is a proof-of-concept that automated, user- friendly CTI is both feasible and valuable.

In conclusion, IntelShield represents a significant step toward accessible, real-time threat intelligence for organizations. Future development will focus on full integration with enterprise security infrastructure and incorporation of advanced AI techniques, further enhancing the platform's capability to preemptively counter cyber threats.

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