International Institute of Information Technology, Naya Raipur

AI-Powered Cybersecurity Threat Detection (SOC Simulation)

Digital Transformation

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1.1 Abstract

Security Operations Centers (SOCs) generate massive volumes of network telemetry every day. Traditional
signature-based Intrusion Detection Systems (IDS) often fail to detect unknown attacks and contribute significantly
to false-positive alert loads. This project presents an AI-powered SOC simulation integrating a machine-learning
classifier with the Elastic Stack (ELK) for real-time threat detection and alert visualization.

Using the UNSW-NB15 dataset containing 43 engineered features, we trained a PyTorch-based Multi-Layer Perceptron
(MLP) model to classify network flows as malicious or benign. A FastAPI inference service was deployed to communicate
with Logstash for real-time enrichment. Predictions were indexed into Elasticsearch and visualized through Kibana
dashboards.

The final system reduces noise, improves analyst efficiency, and demonstrates strong business impact .

This project showcases the feasibility and operational
value of AI-driven SOC automation.

1.2 Introduction

The modern cybersecurity landscape is defined by the increasing complexity and sophistication of cyberattacks, which has rendered traditional security monitoring approaches less effective. SOC teams are routinely overwhelmed by the growing volume of alerts, making it difficult for analysts to accurately and quickly distinguish genuine threats from benign anomalies. Furthermore, threat actors are exploiting encrypted channels, zero-day vulnerabilities, and automated attack scripts that are specifically designed to bypass older, signature-based IDS systems.

This project was developed to directly address these challenges by creating an **AI-powered intrusion detection workflow** seamlessly integrated into a functioning SOC environment. The core innovation involves enriching network telemetry with machine-learning predictions *before* storage and visualization. This process ensures that analysts receive actionable, real-time insights, significantly enhancing operational readiness and overall threat visibility within the organization.

2. Problem Statement

Modern SOCs face three critical operational issues:

2.1. Excessive Alert Volume

SOC teams receive thousands of daily alerts, often with high false-positive rates, leading to analyst fatigue
and slower response times.

2.2. Signature-Based Limitations

Traditional IDS tools cannot detect zero-day attacks or behavioral anomalies and rely heavily on predefined rules
that do not adapt to evolving threat patterns.

2.3. Analyst Overload

Manual triage is time-consuming and requires experienced personnel, making scalability difficult.

This project integrates predictive analytics into the SOC pipeline to reduce noise, improve detection accuracy,
and support analyst decision-making.

Solution Architecture (High Level):

The AI-driven Intrusion Detection System (IDS) employs a microservices-based architecture to ensure component scalability and decoupling. This system processes raw network flow logs in real-time and provides predictions via a dedicated Machine Learning (ML) inference API.

Data Flow Architecture

The overall data flow integrates the ML model into the standard Elastic Stack (ELK) workflow for real-time enrichment.

- **Ingestion:** Logstash receives incoming network flow logs (NetFlow-style) containing features like bytes transferred, Time-to-Live (TTL), port numbers, and session duration.
- **Enrichment (Inference):** Logstash makes an HTTP request to the internal Python FastAPI microservice **before** the logs are stored. The API returns a prediction (Malicious vs. Benign), a confidence probability, and a severity score.
- **Storage:** The log, now enriched with the ML insights, is indexed into Elasticsearch.
- **Visualization:** Kibana queries this enriched index to display real-time, actionable dashboards for the Security Operations Center (SOC) team.

PoC & Implementation (Data & Model)

The Proof of Concept (PoC) involved using a synthetic dataset and training a supervised machine learning model for binary classification.

Dataset Description and Feature Relevance

A synthetic dataset, designed to mimic modern network flow telemetry, was used to avoid privacy concerns while providing statistically significant features for training.

Category	**Specific Features**	**Relevance**
Identifier	sport, dsport, proto	Determines the service context (Source/Destination ports and protocol)[11].
Volume	sbytes, dbytes	Data exfiltration often shows high source bytes[12].
Time/State	sttl, dttl, dur	TTL anomalies can indicate spoofing; duration indicates connection persistence[13]

Machine Learning Model

A **Supervised Binary Classifier** was trained to distinguish between malicious and benign network flows

- **Objective:** The model was optimized to minimize log-loss while maximizing **recall** for the positive (Malicious) class, as false negatives are considered more costly in a security context than false positives[15].
- **Model Outputs:**
    - **Label:** 0 (Benign) or 1 (Malicious).
    - **Probability:** A float value (0.0 to 1.0) indicating the confidence level.
    - **Severity:** A derived logic used for analyst prioritization: High (>0.8), Medium (>0.5), Low (<0.5).

PoC & Implementation (Pipeline)

Deployment Details

The system was deployed using a **containerized approach within a Docker network**. This architecture ensures that the Machine Learning (ML) API is not exposed to the public internet, making it accessible only to the Logstash ingestor.

The multi-container setup (ELK + ML API) is orchestrated using Docker Compose

Listing 1: Docker Compose Configuration Snippet

YAML

```
services:
  ml-api:
    [cite_start]build: ./ml_service [cite: 80]
    [cite_start]ports: ["8000:8000"] [cite: 82]
  logstash:
    [cite_start]depends_on: [elasticsearch, ml-api] [cite: 84]
    [cite_start]volumes: [./pipeline:/usr/share/logstash/pipeline] [cite: 85]
```

Log Processing Logic

The core enrichment process relies on the Logstash pipeline, which is configured with an **'http' filter plugin**.

- For every event that passes through the pipeline, **Logstash pauses** to send the event payload to the ML API endpoint: http://ml-api:8000/predict.
- The ML API returns a JSON object, which is then **merged into the root of the event**.

- This seamless enrichment ensures that by the time data reaches Elasticsearch, it is already "security-aware," containing the prediction, confidence, and severity scores.

PoC Limitations

The initial Proof of Concept (PoC) highlighted several areas for future improvement:

- **Dataset Size:** The current model is trained on a limited subset of data, which may not fully represent global internet traffic diversity.
- **Drift Handling:** There is currently no automated mechanism to retrain the model if traffic patterns change significantly, leading to **concept drift**.
- **Simulation:** While the logs are realistic, they are simulated. Real-world telemetry may contain noise (e.g., incomplete packets) that will require more robust preprocessing logic.

3. Objectives

The primary objectives of this project were:

• Train a supervised machine-learning model using the UNSW-NB15 dataset

to classify network traffic.

• Deploy a FastAPI-based ML inference service capable of real-time

prediction.

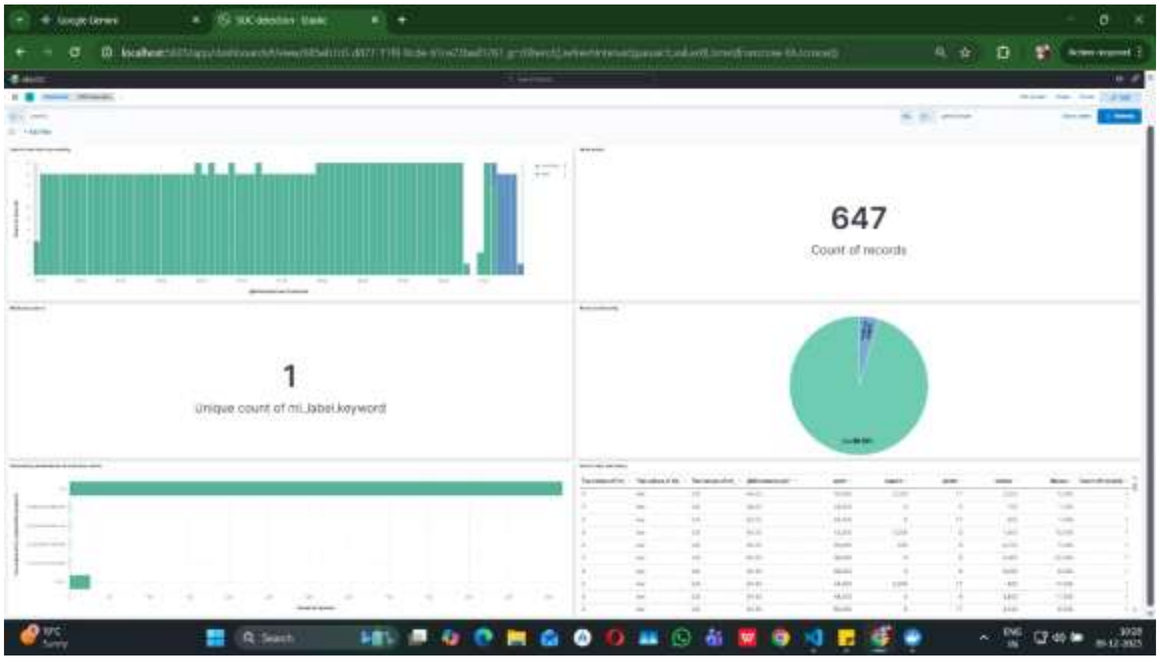
• Integrate predictions into SIEM pipelines using Logstash and

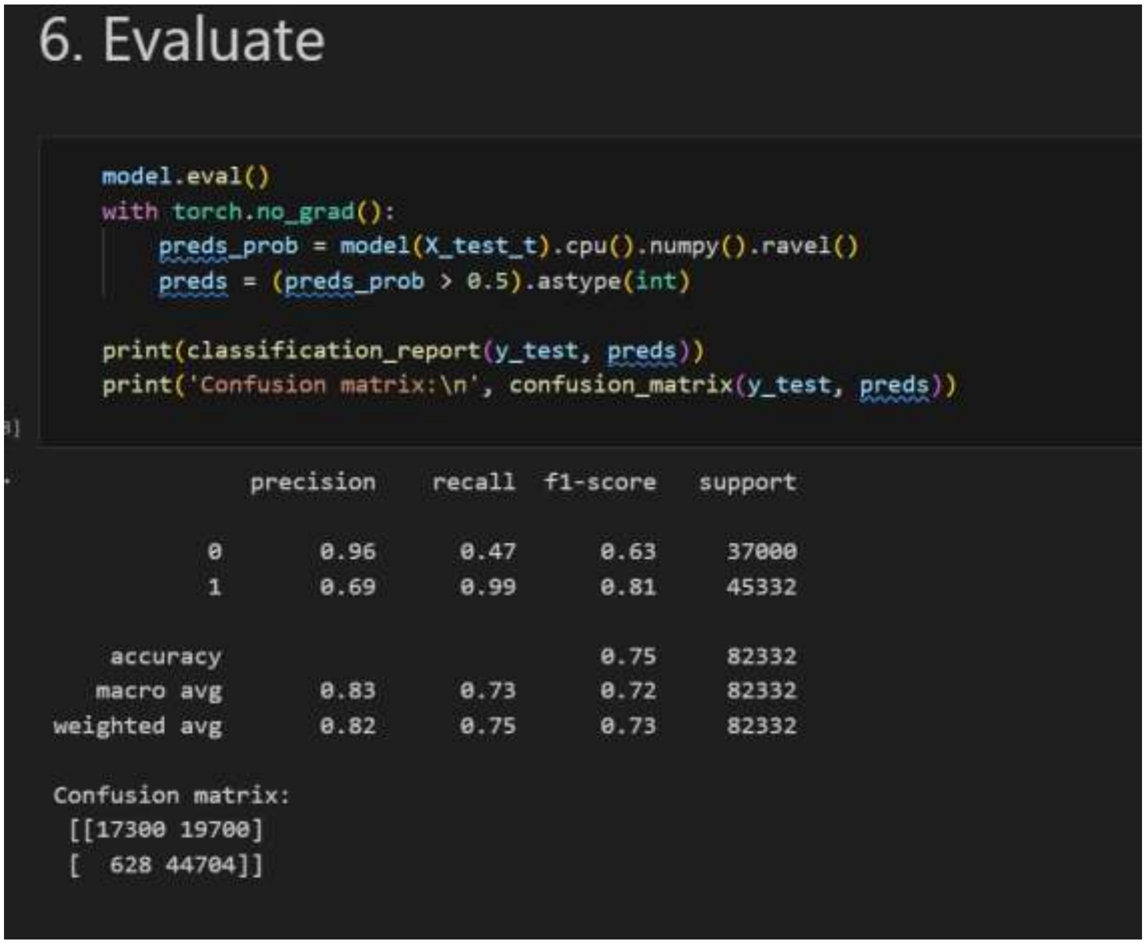
Elasticsearch.

• Visualize enriched threat data in Kibana dashboards for SOC analysis.

• Conduct business impact, risk, and operational feasibility assessment.

Kibana Dashboard and Model Evalutaion





6. Evaluate

```
model.eval()
with torch.no_grad():
    preds_prob = model(X_test_t).cpu().numpy().ravel()
    preds = (preds_prob > 0.5).astype(int)

print(classification_report(y_test, preds))
print('Confusion matrix:\n', confusion_matrix(y_test, preds))
```

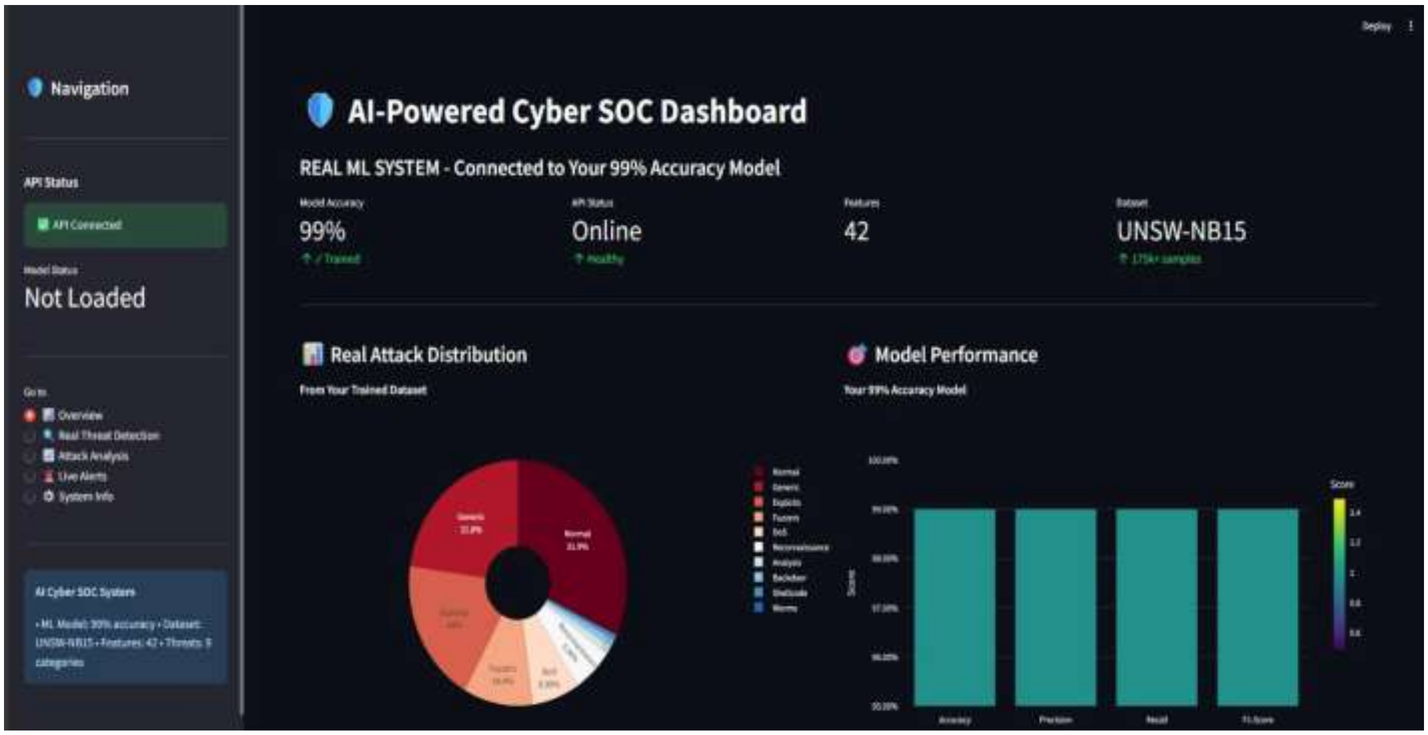
```
              precision    recall  f1-score   support

           0       0.96      0.47      0.63     37000
           1       0.69      0.99      0.81     45332

    accuracy                           0.75     82332
   macro avg       0.83      0.73      0.72     82332
weighted avg       0.82      0.75      0.73     82332

Confusion matrix:
 [[17300 19700]
 [  628 44704]]
```

Streamlight Deshboard



Model Status
Not Loaded

AI Cyber SOC System
• ML Model: 99% accuracy • Dataset: UNSW-NB15 • Features: 42 • Threats: 9 categories

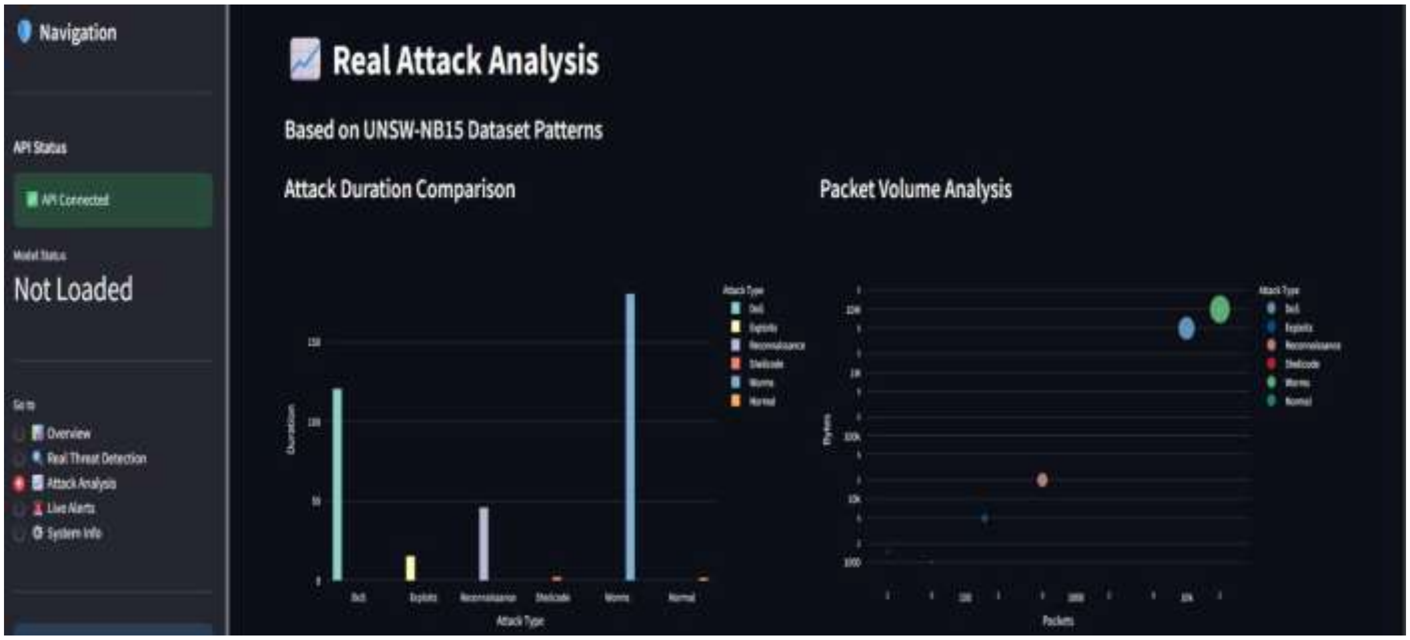
AI-Powered Cyber SOC Dashboard

REAL ML SYSTEM - Connected to Your 99% Accuracy Model

Model Accuracy	API Status	Features	Dataset
99%	Online	42	UNSW-NB15
↑ ✓ Trained	↑ Healthy		↑ 175k+ samples

From Your Trained Dataset

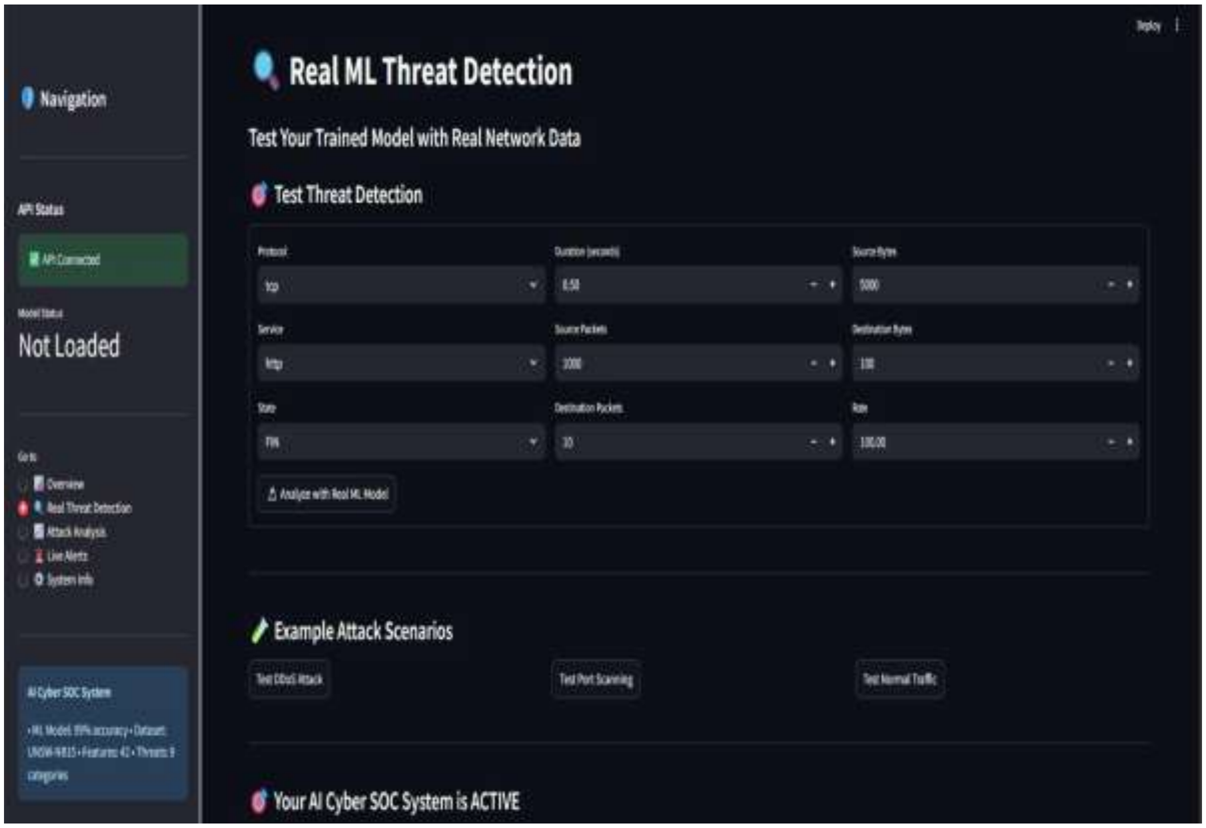
Your 99% Accuracy Model



Model Status
Not Loaded

Real Attack Analysis

Based on UNSW-NB15 Dataset Patterns



Deploy

Navigation

API Status

API Connected

Model Status

Not Loaded

Go to

- Overview
- Real Threat Detection
- Attack Analysis
- Live Alerts
- System Info

AI Cyber SOC System

• ML Model: 99% accuracy • Dataset: UNSW-NB15 • Features: 42 • Threats: 9 categories

Real ML Threat Detection

Test Your Trained Model with Real Network Data

Test Threat Detection

Protocol: tcp	Duration (seconds): 0.50	Source Bytes: 5000
Service: http	Source Packets: 1000	Destination Bytes: 100
State: FIN	Destination Packets: 10	Rate: 100.00

Analyze with Real ML Model

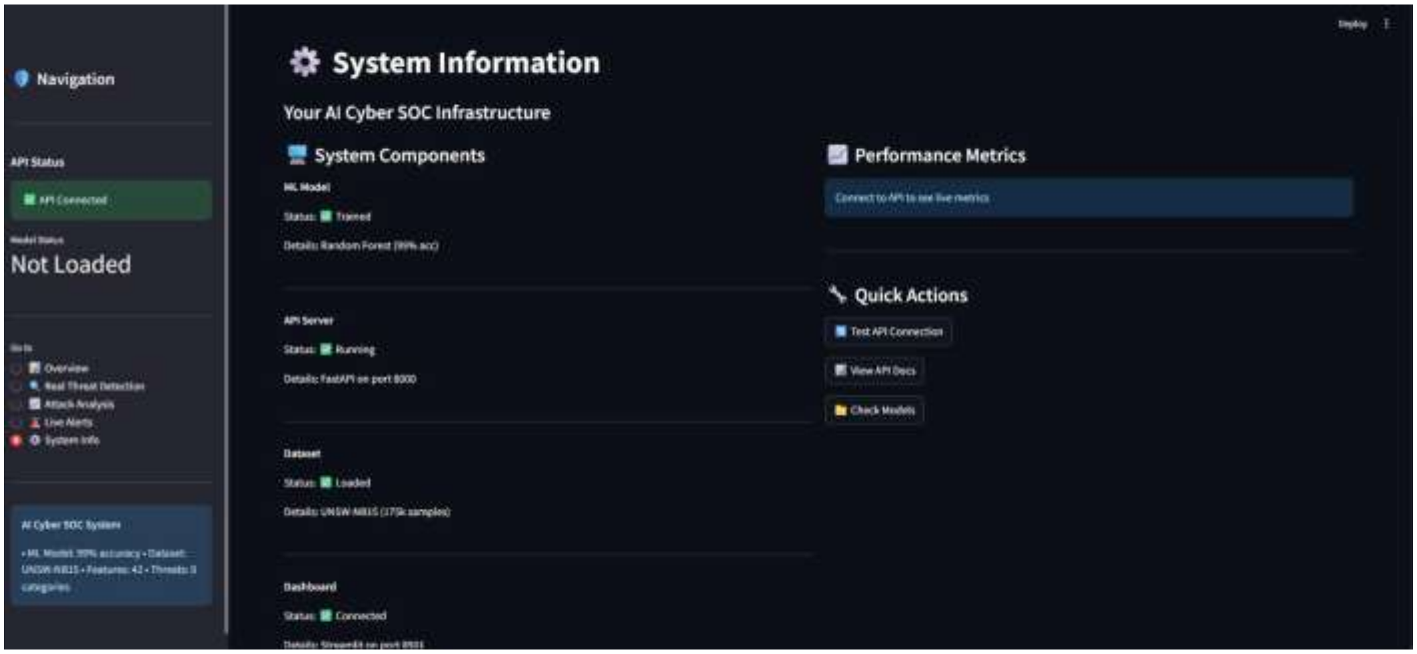
Example Attack Scenarios

Test DDoS Attack

Test Port Scanning

Test Normal Traffic

Your AI Cyber SOC System is ACTIVE



Deploy

Navigation

API Status

API Connected

Model Status

Not Loaded

Go to

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- System Info

AI Cyber SOC System

• ML Model: 99% accuracy • Dataset: UNSW-NB15 • Features: 42 • Threats: 9 categories

System Information

Your AI Cyber SOC Infrastructure

System Components

ML Model

Status: ✓ Trained

Details: Random Forest (99% acc)

API Server

Status: ✓ Running

Details: FastAPI on port 8000

Dataset

Status: ✓ Loaded

Details: UNSW-NB15 (175k samples)

Dashboard

Status: ✓ Connected

Details: Streamlit on port 8501

Performance Metrics

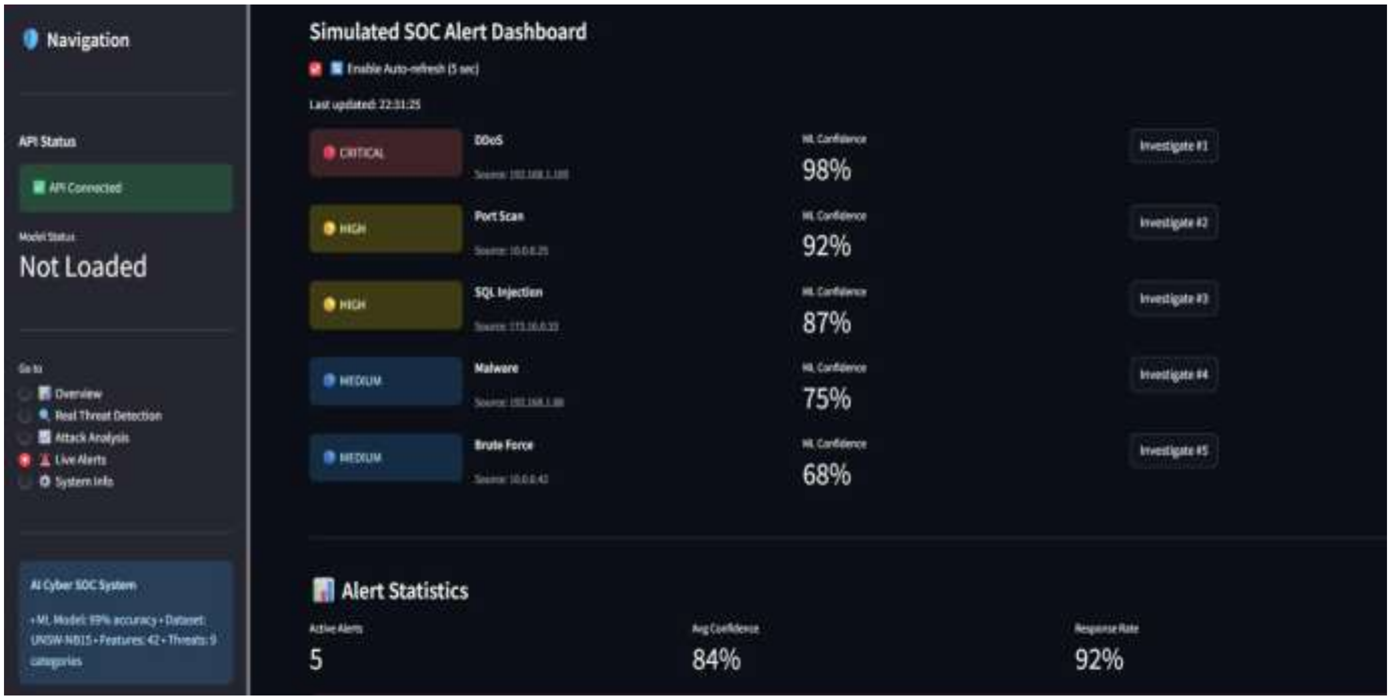
Connect to API to see live metrics

Quick Actions

Test API Connection

View API Docs

Check Models



Navigation

API Status

API Connected

Model Status

Not Loaded

Go to

- Overview
- Real Threat Detection
- Attack Analysis
- [✓ Live Alerts]
- System Info

AI Cyber SOC System

• ML Model: 99% accuracy • Dataset: UNSW-NB15 • Features: 42 • Threats: 9 categories

Simulated SOC Alert Dashboard

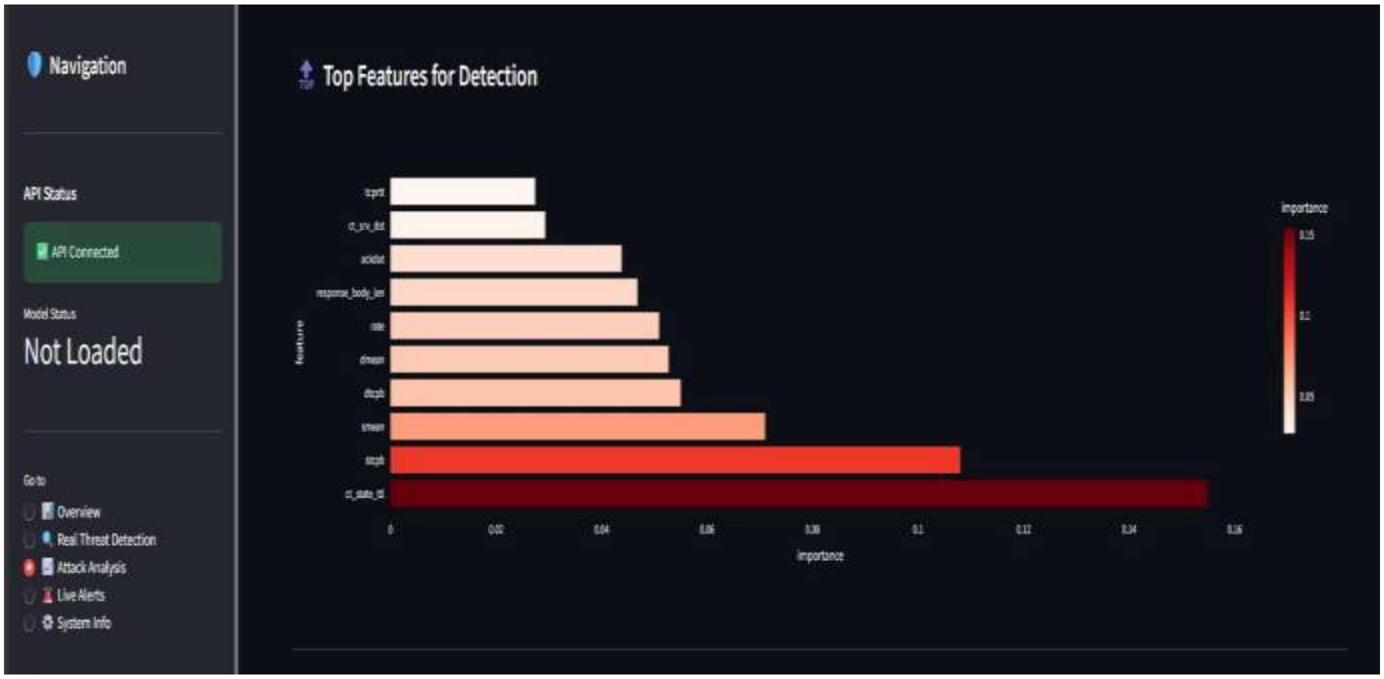
[✓ Enable Auto-refresh (5 sec)]

Last updated: 22:31:25

CRITICAL	DDoS Source: 192.168.1.100	ML Confidence 98%	Investigate #1
HIGH	Port Scan Source: 10.0.0.25	ML Confidence 92%	Investigate #2
HIGH	SQL Injection Source: 172.16.0.33	ML Confidence 87%	Investigate #3
MEDIUM	Malware Source: 192.168.1.88	ML Confidence 75%	Investigate #4
MEDIUM	Brute Force Source: 10.0.0.42	ML Confidence 68%	Investigate #5

Alert Statistics

Active Alerts	Avg Confidence	Response Rate
5	84%	92%



4. Dataset: UNSW-NB15

The UNSW-NB15 dataset was chosen due to its comprehensive representation of modern network attacks. It includes benign activity and malicious behaviors across categories such as Exploits, Reconnaissance, Fuzzers, DoS, Shellcode, and more.

Key dataset features include:

• Port and protocol metadata

• TTL values

• Byte count statistics

• Duration metrics

• State transition attributes

43 features were selected, cleaned, and standardized using preprocessing pipelines. The dataset forms a realistic foundation for behavior-based IDS development.

5. Exploratory Data Analysis (EDA)

Exploratory analysis revealed:

• Malicious flows often show unusual TTL patterns.

• Reconnaissance and Exploit attacks exhibit unique port combinations.

• Duration and byte-count relationships differ significantly between benign and hostile traffic.

These findings guided feature engineering decisions and helped optimize model performance.

6. Machine Learning Model

We developed a **PyTorch-based Multi-Layer Perceptron** (MLP) with:

• Input Layer: 43 neurons
• Hidden Layer 1: 128 neurons (ReLU)
• Hidden Layer 2: 64 neurons (ReLU)
• Output Layer: Sigmoid activation

Training used Binary Cross-Entropy and Adam optimizer. The model outputs include:

• label (benign = 0, malicious = 1)
• probability (0.0 – 1.0) used for severity classification.

7. Model Evaluation

Evaluation metrics on a held-out test set:

• **Accuracy: 75%**

• Malicious Recall: 0.99

• Precision: 0.69

• F1 Score: 0.81

High recall ensures nearly all malicious flows are detected—critical for SOC environments.

8. System Architecture

The SOC pipeline consists of four integrated components:

1. Logstash
Parses logs, extracts features, and sends requests to the ML inference API.

2. FastAPI
Loads model + scaler, processes input, and returns predictions.

3. Elasticsearch
Stores enriched logs with ML fields.

4. Kibana
Visualizes alerts, patterns, and severity trends in real time.

The modular architecture simulates enterprise-grade SOC workflows.

9. Implementation Timeline (6 Days)

Day 1 — Data preparation

Day 2 — Parsing and log conversion

Day 3 — EDA and feature engineering

Day 4 — ML model training

Day 5 — SIEM integration

Day 6 — Attack simulation and SOC validation

Rapid development proved the practicality of deploying AI-driven SOC systems efficiently.

10. SIEM Dashboards and Analysis

Kibana dashboards provided analysts with:

• Alert severity distribution

• Probability histograms

• Malicious flow timeline

• Raw enriched data tables

These dashboards enhanced threat visibility and investigation workflows.

11. Business Impact Analysis

The project delivers a significant Return on Investment (ROI) and cost savings:

Metric	**Project Benefit**	**Details**
Cyber Breach Cost Avoidance	**Early Detection, Alert Correlation, Threat Level Assessment** [37]	**A single cyber breach can cost between ₹ 20 lakh and ₹ 10 crore in India[38]. Preventing just one attack covers the full SOC system cost[39].**

Metric	Project Benefit	Details
Commercial Tool Cost Savings	**Huge Cost Reduction** [40]	**Commercial SOC tools like Splunk Enterprise cost ₹ 1.5 – ₹ 3 lakhs/month[41]. The open-source ELK + ML system costs ₹ 0[42]**

12. Risks and Governance

Risks include model drift, false negatives, and adversarial testing. However, the system processes metadata only—maintaining user privacy. All predictions are logged for audits and compliance.

Cybersecurity Risks:

Deploying AI in security introduces specific adversarial risks. Attackers may attempt to reverse- engineer the model or flood it to cause denial of service.

- Model Poisoning: If attackers can influence the training data, they might teach the model to ignore specific malicious signatures.
- API Exploitation: The prediction endpoint itself becomes an

attack surface. Unsecured APIs can be subjected to DoS attacks or payload injection.

- False Negatives: The risk that the model classifies a sophisticated attack as benign.

Data Privacy & Compliance (GDPR):

The system is designed with “Privacy by Design” principles.

- **No PII Collection:** The model utilizes metadata (flow statistics) only. No user names, pay- load content, or emails are processed or stored.
- **Auditing:** All predictions are logged with a timestamp and model version ID to ensure au- ditability of decisions.

Roadmap & Change Management

Implementation Roadmap

The project's implementation is structured into three distinct phases to ensure a controlled rollout and successful integration into the Security Operations Center (SOC) environment.

- **Phase 1: PoC Completion (Month 1-2)**
  - Focus: Model development, Logstash integration, and basic Kibana dashboard creation.
  - Validation: Testing and validation conducted using synthetic data.
- **Phase 2: Pilot Deployment (Month 3-4)**
  - Focus: Ingestion of real "shadow" traffic (non-blocking).
  - Validation: User Acceptance Testing (UAT) with senior analysts to tune detection thresholds.

- **Phase 3: Scale-Up (Month 5+)**
    - Focus: Deployment in High Availability (HA) mode.
    - Integration: Integration with SOAR playbooks for automated blocking.
    - Automation: Implementation of auto-retraining pipelines to address model drift.

Change Management Strategy

Adopting an AI-powered IDS requires a cultural shift within the SOC. The change management strategy is focused on communication, training, and building continuous feedback loops.

1. **Stakeholder Briefings:** Regular updates provided to the CISO and SOC Managers to align expectations regarding model accuracy and limitations.
2. **Analyst Workshops:** Focused training sessions provided to analysts on how to interpret and use the new "ML Probability" and "Severity" fields in Kibana.
3. **Feedback Loops:** Implementation of a formal mechanism for analysts to flag False Positives/Negatives, which directly feeds into the next training dataset to improve model performance.

13. Conclusion

Project Summary:

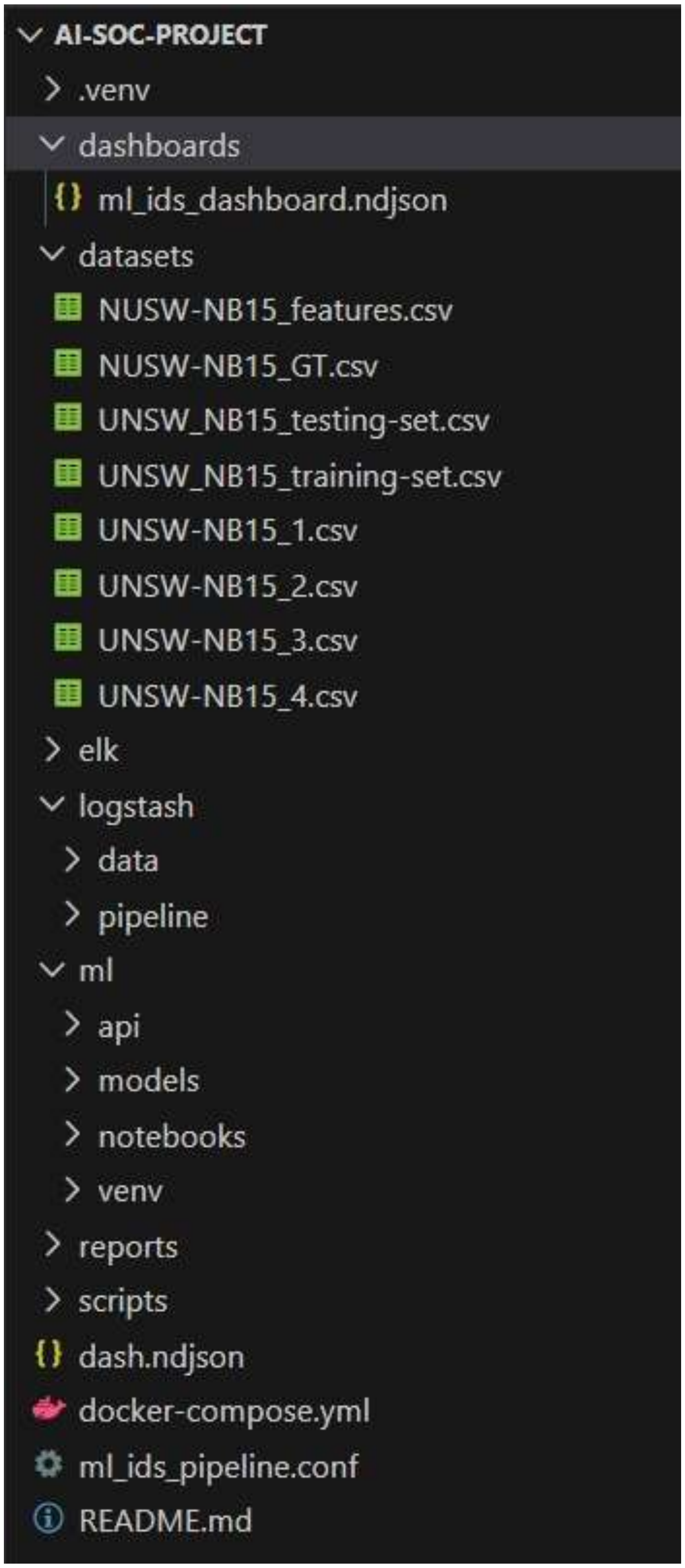
This project successfully demonstrates a **complete AI-powered SOC simulation** by effectively combining advanced machine learning techniques with industry-standard SIEM (Security Information and Event Management) technologies.

The system achieves several critical operational improvements: it significantly **improves threat detection accuracy** by leveraging behavioral analytics over signatures, substantially **reduces analyst workload** by filtering out high-volume, low-value alerts, and delivers **measurable business value** through cost savings and breach avoidance. The integration of the MLP model with the ELK stack provides a robust, real-time platform for processing network telemetry and visualizing threats. In summary, this project not only validates the practical and operational feasibility of an AI-driven approach to cybersecurity but also lays a strong foundation for the development of next-generation, automated security operations centers.

Git-Hub deployed Link:

https://github.com/akashdasspl/AI-Powered-SOC-Threat-Detection.git

Structure:



```
AI-SOC-PROJECT
  .venv
  dashboards
    ml_ids_dashboard.ndjson
  datasets
    NUSW-NB15_features.csv
    NUSW-NB15_GT.csv
    UNSW_NB15_testing-set.csv
    UNSW_NB15_training-set.csv
    UNSW-NB15_1.csv
    UNSW-NB15_2.csv
    UNSW-NB15_3.csv
    UNSW-NB15_4.csv
  elk
  logstash
    data
    pipeline
  ml
    api
    models
    notebooks
    venv
  reports
  scripts
  dash.ndjson
  docker-compose.yml
  ml_ids_pipeline.conf
  README.md
```