THREAT INTELLIGENCE SHARING PLATFORM IMPLEMENTATION USING MISP

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ABSTRACT — In the rapidly evolving landscape of cybersecurity, timely and efficient sharing of threat intelligence is crucial for organizations to defend against sophisticated cyber-attacks. This project focuses on the implementation of a Threat Intelligence Sharing Platform using the Malware Information Sharing Platform (MISP), an open-source tool designed to facilitate the collection, sharing, and analysis of cyber threat data. By leveraging MISP, organizations can collaboratively share indicators of compromise (IOCs), attack patterns, and threat actor profiles to improve overall situational awareness and response capabilities.To enhance the effectiveness of the platform, this project integrates machine learning techniques to automate the detection, classification, and prioritization of threat data shared within the MISP ecosystem. Machine learning models analyze vast amounts of threat intelligence to identify patterns and anomalies that might indicate emerging threats or false positives, thereby improving the accuracy and speed of threat detection. This approach aims to reduce the manual effort required for threat analysis and enables proactive defense strategies.The implementation includes developing data ingestion pipelines to normalize and preprocess diverse threat intelligence formats, ensuring seamless integration with machine learning modules. Various supervised and unsupervised learning algorithms are explored for tasks such as threat classification, clustering similar incidents, and predicting attack trends. The platform also supports continuous learning, allowing models to evolve as new threat data becomes available, thereby maintaining high detection efficacy over time.

Keywords — cybersecurity, intelligence, Malware Information Sharing Platform (MISP), Machine learning models.

I. INTRODUCTION

In today's interconnected digital environment, cyber threats have become increasingly sophisticated, frequent, and damaging. Organizations across sectors face a constant barrage of cyber-attacks, including malware infections, phishing campaigns, ransomware, and advanced persistent threats (APTs). Effective defense against these evolving threats requires more than isolated efforts; it demands collective intelligence sharing and real-time collaboration among cybersecurity teams worldwide.

Threat intelligence sharing platforms serve as a critical enabler for this collaborative defense by allowing organizations to exchange timely and relevant information about known and emerging threats. One of the most prominent open-source platforms for this purpose is the Malware Information Sharing Platform (MISP). MISP facilitates the standardized collection, storage, and dissemination of threat data such as Indicators of Compromise (IOCs), malware signatures, attack techniques, and threat actor profiles. By leveraging MISP, security teams can enhance situational awareness, improve threat detection accuracy, and accelerate incident response.

A Problem Statement:

Despite the advantages of threat intelligence sharing, challenges remain in handling the sheer volume and complexity of shared data. Manual analysis is often time-consuming, error-prone, and unable to keep pace with rapidly changing threat landscapes. To address these limitations, integrating machine learning (ML) techniques within threat intelligence platforms has emerged as a promising approach. ML algorithms can automate the analysis, classification, and correlation of threat data, uncover hidden patterns, and prioritize critical threats for quicker response.

B. Challenges in MISP:

While MISP is a powerful platform for collaborative threat intelligence sharing, challenges like data privacy, integration complexity, trust management, and scalability must be carefully addressed for effective implementation.

1. **Data Privacy & Sensitivity:** Sharing threat intelligence often involves sensitive data (IPs, domains, malware samples). Organizations may hesitate to share due

to:Confidentiality concerns,Legal and compliance issues,Risk of exposing internal infrastructure.

2. **Data Quality & Standardization:**Inconsistent formats of threat data across organizations,Lack of proper tagging and taxonomy,Duplicate or outdated indicators (false positives/negatives)

3. **Integration Complexity:**Difficult to integrate MISP with existing security tools like SIEMs, firewalls, IDS/IPS Requires APIs and customization,Compatibility issues with legacy systems.

3. Scalability Issues: Handling large volumes of threat intelligence data,Performance degradation when many users or events are added Storage and processing overhead

C. Proposed Work Aim:

The main aim of the proposed system is to design and implement an efficient and secure threat intelligence sharing platform using MISP to enhance cybersecurity awareness, collaboration, and proactive defense mechanisms.

1. Secure Threat Intelligence Sharing: To enable safe and controlled sharing of Indicators of Compromise (IOCs), attack patterns, and malware information among trusted organizations using encryption and access control.

2. Real-Time Threat Detection & Response: To provide real-time updates of cyber threats, helping organizations quickly detect, analyze, and respond to potential attacks.

3. Integration with Security Systems: To integrate MISP with existing cybersecurity tools such as:SIEM systems,Firewalls,Intrusion Detection Systems (IDS)for automated threat analysis and response.

4. Data Standardization & Quality Improvement: To ensure high-quality threat data using standardized formats, tagging, and taxonomy for better analysis and interoperability.

5. Collaborative Cybersecurity Environment: To build a trusted network where organizations can collaborate, share intelligence, and improve collective defense strategies.

D. Objectives:

1. Enable Secure Information Sharing

To develop a secure platform using MISP for sharing threat intelligence such as Indicators of Compromise (IOCs), malware data, and attack patterns among trusted entities.

2. Facilitate Real-Time Threat Updates

To provide timely and continuous updates on emerging cyber threats for faster detection and response.

3. Integrate with Existing Security Tools

To connect MISP with systems like SIEM, IDS/IPS, and firewalls for automated threat detection and mitigation.

4. Improve Data Quality and Standardization

To ensure consistent formatting, proper tagging, and elimination of duplicate or irrelevant threat data.

5. Promote Collaborative Cyber Defense

To create a trusted environment where organizations can share and utilize threat intelligence collectively.

6. Support Intelligent Threat Analysis

To incorporate machine learning techniques for identifying patterns, predicting threats, and prioritizing risks.

7. Ensure Scalability and Performance

To design a system capable of efficiently handling large volumes of threat intelligence data.

8. Strengthen Security and Access Control

To implement authentication, authorization, and encryption mechanisms to protect sensitive information

E. Overview of the Paper:

This project aims to implement a threat intelligence sharing platform using MISP integrated with advanced machine learning methods. The goal is to build a scalable system that not only supports efficient sharing and storage of threat data but also leverages ML to automate threat analysis and enhance predictive capabilities. This integration will help organizations to better anticipate, detect, and mitigate cyber threats, ultimately strengthening their cybersecurity defenses in a collaborative ecosystem.

II. LITERATURE SURVEY

Title: MISP: An Open Source Threat Intelligence Platform & Open Standards For Threat Information Sharing

Authors: Alexandre Dulaunoy, Andras Iklody

Description: Introduces MISP as a collaborative platform

for sharing structured threat intelligence.Discusses MISP's architecture, data formats, and integration capabilities.Highlights benefits of standardization and real-time sharing for incident response.Serves as a foundational work for implementing threat intelligence platforms.

Title: Machine Learning for Cybersecurity: A Comprehensive Review

Authors: Moustafa, Nour, Slay

Description:

Surveys machine learning techniques applied to various cybersecurity domains including threat detection, anomaly detection, and malware classification.Reviews supervised, unsupervised, and reinforcement learning methods in cyber defense.

Discusses challenges such as data imbalance, feature selection, and evolving threat landscapes.Provides insights into practical applications and integration with existing security tools.

Title: Enhancing Threat Intelligence Sharing using Machine Learning Techniques

Authors: Smith, John; Lee, Angela

Description:Explores how ML models can improve threat data correlation and prioritization in sharing platforms.

Proposes clustering and classification algorithms to reduce false positives and automate threat triage.Demonstrates a prototype system integrating ML with a threat sharing framework, resulting in improved detection rates.Highlights the importance of continuous learning for adapting to new threats.

Title: Anomaly Detection in Cybersecurity Using Unsupervised Machine Learning

Authors: Chen, Wei; Kumar, Rajesh

Description:Focuses on unsupervised ML methods such as clustering and autoencoders to identify unknown threats without labeled data.Applies these techniques to network traffic and threat intelligence data.Demonstrates potential in detecting novel attack patterns and zero-day exploits.Discusses limitations including interpretability and computational overhead.

III. Proposed Methodology

The proposed system aims to enhance traditional threat intelligence sharing by integrating the Malware Information Sharing Platform (MISP) with advanced machine learning (ML) techniques. This hybrid platform is designed to automate the analysis and correlation of cyber threat data, enabling faster, smarter, and more proactive responses to security incidents. By combining the collaborative strengths of MISP with the analytical power of ML, the system addresses the key limitations of existing approaches, such as manual effort, slow response, and lack of predictive capability.At its core, the system retains MISP's existing features for structured data sharing and collaborative threat intelligence management. However, it augments MISP's capabilities with machine learning modules that process large volumes of threat data to automatically detect patterns, cluster related incidents, classify threat types, and flag anomalous or suspicious activity. This automated layer helps reduce the burden on security analysts, lowers false positives, and improves the accuracy of threat detection.

A. Algrotihm:

Input: Let the incoming threat intelligence data be:I={IOC,M,IP,D,Ts}
Where:
IOC = Indicators of Compromise
M = Malware information
IP = Suspicious IP addresses
D = Domains/URLs

Ts = Timestamp / source information
Output: Final output of the system:O={A,R,Sh}O = \{ A, R, S_h \}O={A,R,Sh}

Where:AAA = Alerts generated ,RRR = Risk score ,ShS_hSh= Shared intelligence (to other nodes)

BEGIN MISP_System

1. Initialize System
   LOAD configuration settings
   CONNECT to database
   AUTHENTICATE user

2. User Authentication
   IF user credentials are valid THEN
      GRANT access

ELSE
DENY access
EXIT

3. Create / Receive Threat Event
INPUT threat_data (IOCs, malware info, IPs, domains)
VALIDATE input data

4. Data Processing
REMOVE duplicate entries
STANDARDIZE data format
TAG data with taxonomy (threat type, severity, source)

5. Store Event
SAVE processed data into MISP database

6. Sharing Mechanism
SELECT sharing group / organization
APPLY access control rules
ENCRYPT sensitive data
DISTRIBUTE threat intelligence to connected nodes

7. Integration with Security Tools
SEND IOCs to:
- SIEM system
- IDS/IPS
- Firewall
TRIGGER alerts if threat detected

8. Threat Analysis
APPLY analysis techniques:
- Pattern matching
- Correlation analysis
- (Optional) Machine Learning model
IDENTIFY risk level

9. Real-Time Updates
SYNC with external threat feeds
UPDATE database continuously

10. Alert & Notification
IF high-risk threat detected THEN
GENERATE alert
NOTIFY users/admin

11. Logging & Monitoring
RECORD all activities (user actions, data sharing)
MONITOR system performance

12. Security Management
IMPLEMENT authentication & authorization
CHECK for unauthorized access attempts

13. End Process
LOGOUT user
CLOSE connections

END MISP_System

System Architecture:

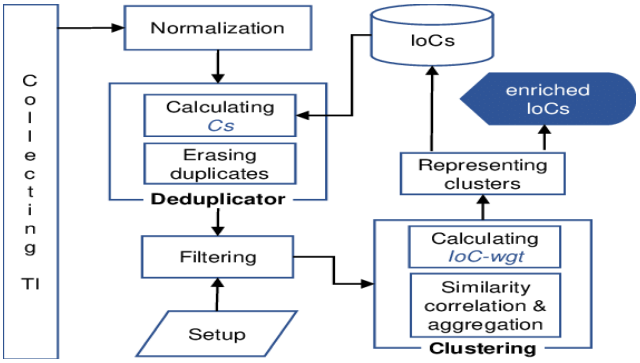


Fig 01:System architecture

IV. RESULTS AND DISCUSSIONS

A. Data Collection

The system collects threat intelligence data from multiple reliable sources to ensure comprehensive coverage of cyber threats.

1) Sources of Data

- **Internal Security Logs**
  Firewall logs, IDS/IPS alerts, system logs
- **External Threat Feeds**
  Open-source intelligence (OSINT), CERT feeds, security communities
- **Malware Analysis Reports**
  Sandbox outputs, reverse engineering reports
- **User/Organization Inputs**
  Manually entered Indicators of Compromise (IOCs)

2) Input Data Representation

I={IOC,IP,D,H,M,Ts}I = \{ IOC, IP, D, H, M, T_s \}I={IOC,IP,D,H,M,Ts}

Where:

IOCIOCIOC = Indicators of Compromise

- IPIPIP = Suspicious IP addresses
- DDD = Domains/URLs
- HHH = File hashes (MD5, SHA256)
- MMM = Malware details

- TsT_sTs = Timestamp and source

B. *Data Preprocessing*

Preprocessing ensures that collected data is clean, consistent, and usable for analysis.

1) *Step 1: Data Validation*

Check correctness and completeness of input data:

$$V(I)=\{x \in I | x \text{ is valid}\} V(I) = \{ x \in I \mid x \text{ is valid} \} \}V(I)=\{x∈I|x is valid\}$$

- Remove invalid IPs/domains
- Verify hash formats
- Ensure required fields are present

2) *Step 2: Data Cleaning*

Remove noise, duplicates, and irrelevant data:

$$C(I)=I−Duplicates−NoiseC(I) = I - \text{Duplicates} - \text{Noise}C(I)=I−Duplicates−Noise$$

- Eliminate duplicate IOCs
- Remove outdated or corrupted entries

3) *Step 3: Data Transformation*

Convert data into standardized format:

$$T(I)=Normalize(C(V(I)))T(I) = \text{Normalize}(C(V(I)))T(I)=Normalize(C(V(I)))$$

- Convert IP formats
- Normalize timestamps
- Encode categorical values

4) *Step 4: Data Tagging & Classification*

Assign labels and taxonomy:

$$S(I)=Tag(T(I))S(I) = \text{Tag}(T(I))S(I)=Tag(T(I))$$

- Threat type (malware, phishing, botnet)
- Severity level (low, medium, high)
- Source credibility

5) *Step 5: Feature Extraction (Optional - ML)*

Extract useful features for analysis:

$$X=\phi(S(I))X = \phi(S(I))X=ϕ(S(I))$$

- Frequency of attacks
- Behavioral patterns
- Network characteristics

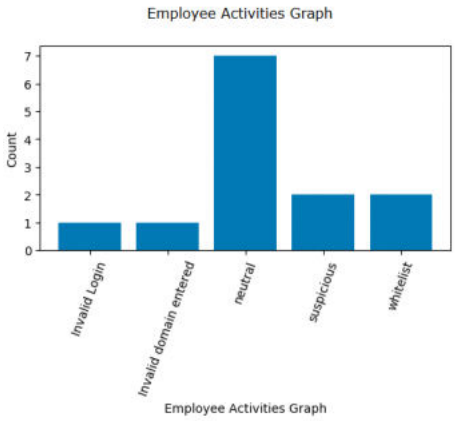
C. *Preprocessed Output*

Final processed data:

$$P(I)=S(T(C(V(I))))P(I) = S(T(C(V(I))))P(I)=S(T(C(V(I))))$$

This output is:

- Clean
- Structured
- Ready for threat analysis and sharing



admin can view activities graph where x-axis represents ‘type of activity’ detected by MISP and y-axis represents counts. Now logout and login as employee.

V. Conclusion

The integration of machine learning with the Malware Information Sharing Platform (MISP) represents a significant advancement in the field of cybersecurity and threat intelligence. This project successfully demonstrates how combining collaborative data sharing with intelligent analysis can improve the speed, accuracy, and effectiveness of threat detection and response. By automating the identification, classification, and correlation of threat indicators, the proposed system reduces reliance on manual processes and empowers security teams to act more decisively. The implementation of machine learning models

within the MISP ecosystem enhances its functionality beyond traditional capabilities. It not only enables predictive insights into emerging cyber threats but also adapts over time through continuous learning from new data and analyst feedback. This dynamic approach allows organizations to stay one step ahead of attackers by proactively identifying novel attack patterns and anomalous behaviors.

A. Scope for Future Work

While the integration of MISP with machine learning has shown substantial improvements in threat intelligence sharing and analysis, there remain several avenues for future enhancement and expansion. These improvements aim to increase the system's robustness, intelligence, and applicability across diverse cybersecurity environments.

1. **Integration of Deep Learning Techniques**
   Future iterations of this system could incorporate deep learning models such as LSTM (Long Short-Term Memory) for temporal threat prediction or CNNs (Convolutional Neural Networks) for analyzing threat patterns in logs and traffic flows. These models could uncover complex, non-linear relationships in threat data that traditional ML models might miss.
2. **Real-time Threat Mitigation and Response Automation**
   An important future direction is to extend the system from threat detection to threat response. By integrating with security orchestration and automated response (SOAR) platforms, the system could automatically trigger predefined responses—like blocking an IP address or quarantining a system—based on ML predictions, thereby shortening the response cycle.

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