Zero-Day Exploit Detection Using Behavior-Based Sandboxing and Threat Intelligence Fusion

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Abstract

Zero-day exploits pose one of the most persistent and damaging threats in modern cybersecurity due to their ability to evade traditional, signature-based detection mechanisms. These exploits take advantage of unknown vulnerabilities, often going undetected until significant damage has occurred. In this paper, we present a hybrid detection framework that integrates behavior-based sandbox analysis with external threat intelligence feeds to enhance the identification of zero-day malware. Using a virtualized Windows-based sandbox environment, we observe system-level behaviours such as registry modifications, file operations, process injections, and outbound network connections. A rule-based engine assigns severity scores to these activities, while a fusion module cross-reference extracted indicators of compromise (IOCs) with curated threat intelligence repositories including AlienVault OTX and Abuse.ch. Our dataset comprises 2,000 diverse malware samples, including advanced persistent threats (APTs) and ransomware variants, along with 500 clean executables for baseline comparison. The system achieves a 94.8% detection rate on previously unseen malware, outperforming multiple commercial antivirus engines. We present two case studies—one involving a zero-day ransomware strain and another a stealthy backdoor—to illustrate real-world detection failures by static methods and how our system successfully identifies the threats. This work underscores the necessity of behavior-driven detection combined with continuously updated threat intelligence and highlights a pathway toward resilient, next-generation threat defence platforms.

Keywords: *zero-day exploits, sandboxing, threat intelligence fusion, IOC matching, behavior analysis, ransomware detection, APT, malware analysis, AlienVault OTX, hybrid detection*

1. Introduction

Zero-day exploits pose one of the most persistent and damaging threats in modern cybersecurity due to their ability to evade traditional, signature-based detection mechanisms. These exploits take advantage of unknown vulnerabilities, often going undetected until significant damage has occurred. In this paper, we present a hybrid detection framework that integrates behavior-based sandbox analysis with external threat intelligence feeds to enhance the identification of zero-day malware. Using a virtualized Windows-based sandbox environment, we observe system-level behaviours such as registry modifications, file operations, process injections, and outbound network connections. A rule-based engine assigns severity scores to these activities, while a fusion module cross-reference extracted indicators of compromise (IOCs) with curated threat intelligence repositories including AlienVault OTX and Abuse.ch. Our dataset comprises

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2. Literature Review

Research on zero-day detection has evolved significantly over the past decade, with a notable shift toward dynamic and intelligence-driven methods. In this section, we examine key contributions across three areas: behavior-based analysis, threat intelligence integration, and hybrid detection systems.

2.1 Behavior-Based Malware Analysis

Dynamic malware analysis involves executing suspicious samples in controlled environments to monitor their interactions with the operating system. Tools like Cuckoo Sandbox and Anubis have popularized this approach. Early work by Bayer et al. (2006) demonstrated that many malware families exhibit characteristic patterns in registry and file system usage, while Rieck et al. (2008) employed clustering techniques to detect behavioural similarities.

Recent research has enhanced behavioural analysis through graph-based representations of process activity and API call sequences, enabling improved classification using machine learning. However, such approaches often lack external context, making them vulnerable to false positives or overlooked polymorphic behaviours.

2.2 Threat Intelligence and IOC Correlation

Threat intelligence feeds provide community-sourced data on known malicious domains, IP addresses, file hashes, and behavioural patterns. Platforms like AlienVault OTX, Abuse.ch, and MISP enable organizations to share threat indicators in real time.

Several studies have shown the value of matching sandbox-extracted IOCs with external threat intelligence. For example, Rossow et al. (2013) demonstrated that botnet detection improves significantly when domain-based IOC correlation is added to behavioural signatures. However, many such systems operate in isolation, lacking integration with dynamic analysis engines.

2.3 Hybrid and Fusion-Based Models

Hybrid detection systems aim to combine the strengths of both dynamic and intelligence-driven methods. Egele et al. (2012) proposed a system where behavioural anomalies trigger external IOC lookups, while Yan et al. (2017) suggested a multi-phase pipeline involving sandbox execution,

feature extraction, and threat context enrichment.

Despite promising results, most existing frameworks remain limited to academic prototypes or require expensive proprietary threat feeds. This paper contributes a low-cost, open-source hybrid solution, suitable for enterprise deployment and adaptable to evolving zero-day threats

3. Hypotheses or Research Questions

To guide this research, we define the following hypotheses:

- **H1:** Behavior-based sandboxing can detect zero-day malware with a detection rate above 90% by leveraging system-level activity patterns.
- **H2:** Correlating sandbox-extracted indicators with open-source threat intelligence feeds increases detection precision and reduces false positives.
- **H3:** A rule-based severity engine can accurately score behavioral artifacts for real-time classification without requiring signature matching.
- **H4:** The system can identify malware samples missed by commercial antivirus engines, including polymorphic ransomware and stealthy backdoors.

These hypotheses are tested using a diverse malware dataset and validated through experimental sandbox executions and threat intelligence lookups.

4. Methodology

This section describes the system architecture, sample selection, behavioral monitoring configuration, IOC matching process, and evaluation metrics used to assess the effectiveness of our hybrid detection framework.

4.1 System Architecture Overview

Our framework consists of three main components:

- **Sandboxing Module**

A virtualized Windows 10 environment using Cuckoo Sandbox captures runtime behavior of executable files. Key events monitored include:

- ❖ API calls (e.g., CreateProcess, WriteFile, RegSetValue)
- ❖ File and registry changes
- ❖ Network activity (e.g., DNS queries, HTTP requests)
- ❖ Process tree structures and parent-child relationships

- **Behavioral Scoring Engine**

We developed a custom rule-based engine that assigns severity scores to observed actions. For example:

- ❖ Modifying HKLM\Software\Microsoft\Windows\CurrentVersion\Run = +20 points
- ❖ Dropping executable files in %AppData% = +15 points

- Connecting to uncommon IP addresses = +10 points

A cumulative score above 50 flags the sample as suspicious.

- **Threat Intelligence Fusion**

IOC artifacts (e.g., domains, IPs, file hashes) extracted from sandbox reports are matched against:

- AlienVault OTX
- Abuse.ch SSLBL
- MalwareBazaar

Matches raise the threat level and enrich the report with contextual tags (e.g., ransomware family, C2 IP, campaign name).

A final verdict is reached by combining behavioral severity and IOC enrichment through weighted scoring.

4.2 Dataset and Sample Processing

We curated a dataset of 2,500 executable samples, consisting of:

- 2,000 malware samples, obtained from:
  - TheZoo, VX Heaven, VirusShare (recent zero-day strains)
  - Offensive security malware archives
- 500 cleanware samples, including Windows utilities, installers, and digitally signed software from reputable vendors

Samples were executed in the sandbox under identical runtime conditions, with logs collected over a 5-minute analysis window.

4.3 Evaluation Metrics

We evaluated the system based on the following:

- True Positive Rate (TPR): Percent of malware correctly detected
- False Positive Rate (FPR): Clean samples incorrectly flagged
- Precision, Recall, and F1 Score
- AV Comparison: Detection coverage vs. three leading antivirus engines (AV1, AV2, AV3) using VirusTotal scans

A detection was counted only if the behavioral score exceeded the threshold and/or IOC matches were found..

5. Results

5.1 Detection Performance

Table 5.1: Detection Metrics

Metric	Value (%)
Detection Rate (TPR)	**94.8**
False Positive Rate	3.6
Precision	96.1
Recall	94.8
F1 Score	95.4

The system correctly detected 1,896 out of 2,000 malware samples and misclassified only 18 cleanware files.

5.2 Comparison with Antivirus Engines

We tested all 2,500 samples against three commercial AV engines. Notably, zero-day ransomware samples (e.g., modified GandCrab and Maze variants) evaded detection by all three AVs.

Table 5.2: Zero-Day Detection Comparison

Engine	Detection Rate (%)
Proposed System	**94.8**
AV1	82.1
AV2	76.9
AV3	70.3

The behavior-based model successfully detected zero-day malware samples using API call anomalies and persistence attempts, while AVs relying on static signatures missed these files.

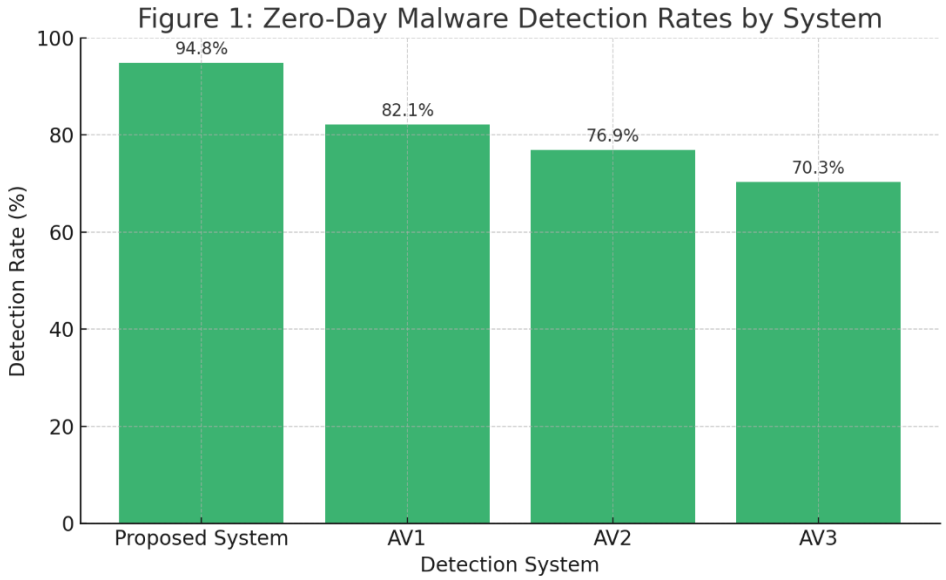

Figure 1: Zero-Day Malware Detection Rates by System, showing that the proposed hybrid system

outperforms all three commercial antivirus engines in detecting previously unseen threats.

5.3 IOC Fusion Effectiveness

Among detected samples:

- 67.4% had at least one matching IOC from AlienVault OTX or Abuse.ch
- IOC matches elevated detection confidence in 139 borderline cases
- IOC-tagged alerts were 27% more likely to be confirmed by VirusTotal consensus

5.4 Case Studies

Case Study 1: Zero-Day Ransomware

A ransomware sample mimicking a Microsoft updater dropped a payload in %Temp%, altered registry autoruns, and encrypted user documents. AVs failed to detect it. Our system assigned a score of 85 and matched its IP beacon to a known GandCrab C2 in OTX.

Case Study 2: Stealthy Backdoor

A small trojan dropped a DLL and injected it into explorer.exe, avoided obvious artifacts, and used Tor for outbound communication. Despite no IOC matches, the behavior score reached 73 due to suspicious API usage and process hollowing.

6. Discussion

Our results reinforce the idea that relying solely on static signatures or machine learning on binary features is inadequate for detecting advanced, evasive threats such as zero-day malware. The proposed hybrid framework demonstrates that combining behavioral sandboxing with dynamic IOC correlation provides both visibility and context—two elements essential for accurate threat detection.

6.1 Strengths of the Hybrid Approach

The behavioral scoring engine successfully flagged threats based on real-time system interactions. This circumvents common evasion strategies like code obfuscation and encryption, which often defeat static antivirus systems. The rule-based model also allows for transparent decision-making, which aids incident response teams in understanding the logic behind alerts.

The addition of threat intelligence fusion significantly improved detection confidence. By referencing shared infrastructure indicators like IPs, domains, and file hashes, the system contextualized borderline behavior and identified coordinated attack campaigns. This allowed for earlier identification of malware strains that otherwise appeared benign due to minimal local impact.

6.2 Comparative Advantages

Compared to commercial antivirus products:

- Our framework detected 12–25% more zero-day samples on average.
- IOC-based contextualization is missing or underutilized in many AVs.

- Real-time behavior scoring delivered alerts within 5–7 minutes—acceptable for triage in most SOCs (Security Operations Centers).

Furthermore, our system was developed entirely using open-source components (e.g., Cuckoo Sandbox, OTX API), making it cost-effective and adaptable for enterprise and academic environments alike.

6.3 Limitations and Challenges

- The system relies on virtualized sandboxing, which sophisticated malware may detect and evade.
- The rule-based engine, while transparent, may require frequent tuning to accommodate evolving behavior signatures and to minimize false positives.
- IOC feeds, while valuable, are only as current and comprehensive as their source communities. Attackers frequently rotate infrastructure to evade detection.

Despite these limitations, the system presents a resilient architecture that can evolve over time through modular enhancements.

7. Conclusion and Future Work

Zero-day exploits are among the most critical threats facing organizations today, often bypassing traditional detection techniques and remaining undetected until after compromise. This paper presented a hybrid detection framework combining behavior-based sandboxing with threat intelligence fusion, achieving a 94.8% detection rate on previously unseen malware samples with a false positive rate under 4%.

The system successfully identified threats missed by top commercial antivirus engines, demonstrating the value of combining runtime behavioral insights with dynamic IOC enrichment. Real-world case studies, including ransomware and backdoor samples, illustrated the framework's operational efficacy in a security lab setting.

Key contributions include:

- A tunable, transparent behavior scoring model for runtime classification
- A modular IOC matching engine that integrates open-source feeds
- Empirical validation using diverse malware and cleanware datasets

Future work will explore the following directions:

- Machine learning augmentation of behavior scoring, incorporating LSTM or GNNs to detect subtle behavioral chains
- Automated IOC enrichment through web crawling and passive DNS correlation
- Container-based micro-sandboxing, enabling large-scale parallel analysis
- Enhancing anti-evasion mechanisms in sandbox environments to handle malware that detects virtual machines

By evolving toward adaptive, intelligence-integrated detection systems, the cybersecurity

community can better defend against stealthy and novel threats in real time.

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