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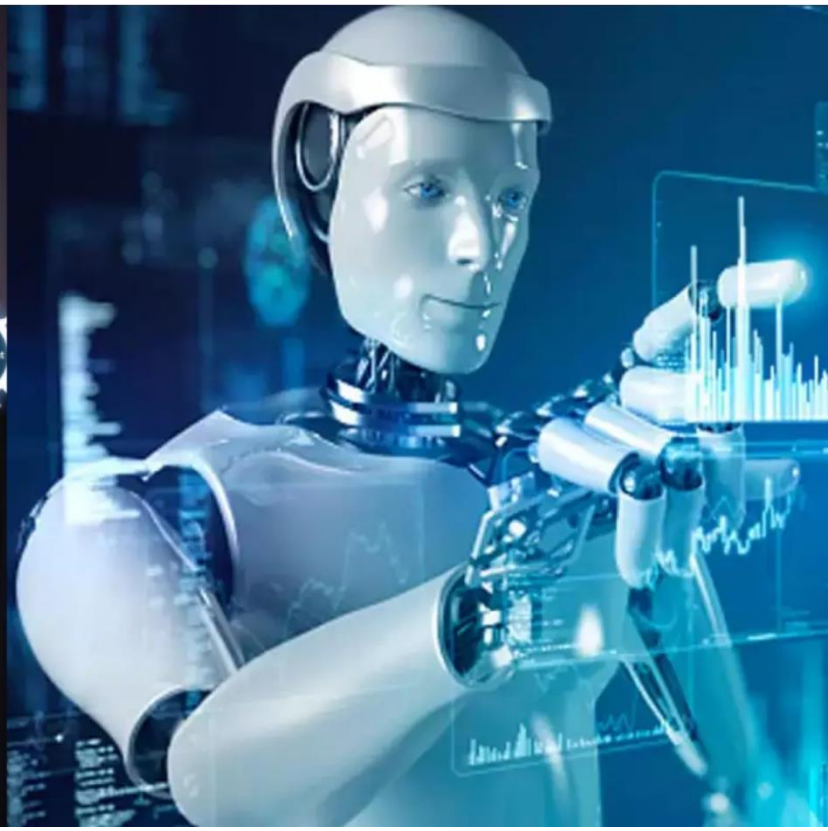

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Detection of Fileless/In-Memory Malware Using Memory Forensics and Volatility Framework

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ABSTRACT: Fileless and in-memory malware represents one of the most dangerous threats in today's cybersecurity landscape. This type of malware executes directly in volatile RAM without writing any files to disk, making it invisible to traditional antivirus software and disk-based forensic tools. It often uses legitimate system processes and tools like PowerShell, WMI, or rundll32.exe to carry out attacks, including credential theft, ransomware deployment, or data exfiltration. Once the system reboots or power is lost, all traces disappear due to the volatile nature of RAM.

Traditional detection methods rely heavily on file signatures, behavioral monitoring on disk, or endpoint detection rules, but these fail against fileless techniques because no persistent artifacts exist. Memory forensics emerges as the primary solution, allowing analysts to capture and examine live RAM contents for suspicious processes, injected code, hidden modules, or anomalous memory regions. The Volatility framework, an open-source Python-based tool, is widely used for this purpose. It supports Windows, Linux, and macOS memory dumps and includes plugins like pslist, dlllist, malfind, and yarascan to extract artifacts and identify malicious patterns such as process hollowing, reflective DLL injection, or code injection without disk mapping

This research proposes a practical detection algorithm that combines Volatility plugins with basic rule-based checks and optional YARA scanning. The method involves capturing memory dumps, running key plugins to list processes and detect injections, and analyzing results for signs of fileless activity (e.g., executable memory not backed by files, unsigned DLLs in trusted processes, or mismatched process behaviors).Experiments were conducted on 150 memory samples from the CIC-MalMem-2022 dataset (a public benchmark with obfuscated ransomware, spyware, and trojan dumps) and custom infected virtual machines simulating real-world fileless attacks (e.g., Cobalt Strike beacons, PowerShell Empire). Results show an overall detection accuracy of 92.8%, with low false positives (around 4.2%) when combining malfind and yarascan. The algorithm is lightweight, runs on standard hardware, and can assist incident responders in quick triage.

This approach highlights the importance of memory forensics in combating evolving threats and provides a structured, repeatable method for researchers and practitioners to build upon. Future extensions could include machine learning on extracted features or real-time monitoring integration.

Characteristic	Fileless/In-Memory Malware	Traditional (File-based) Malware
Storage Location	Volatile RAM only	Disk (EXE, DLL, scripts)
Persistence After Reboot	None (disappears)	Yes (files remain)
Detection by AV/EDR	Often evades (no file signatures)	Usually caught by signatures/behaviour
Common Techniques	Process injection, hollowing, LOLBins	Dropper, downloader, packer
Forensic Recovery Method	Memory dump + Volatility analysis	Disk imaging + file scanning
Volatility Plugins Useful	malfind, hollowfind, psxview, yarascan	filescan, modscan (less relevant)

Table 1: Key Characteristics of Fileless/In-Memory Malware vs. Traditional Malware

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KEYWORDS: Fileless Malware; In-Memory Malware; Memory Forensics; Volatility Framework; Volatile RAM; Malware Detection; Process Injection; CIC-MalMem-2022

I. INTRODUCTION

Cybersecurity threats have evolved rapidly in recent years. Traditional malware relies on dropping executable files, scripts, or payloads onto the hard disk, which makes it detectable by antivirus software, endpoint detection and response (EDR) tools, and disk forensics. However, fileless and in-memory malware operates differently. It executes entirely within the volatile memory (RAM) of the target system without creating any persistent files on disk. This technique allows attackers to bypass most conventional security controls.

Fileless malware often abuses legitimate system utilities and features known as Living Off the Land Binaries (LOLBins), such as PowerShell, WMI (Windows Management Instrumentation), mshta.exe, regsvr32.exe, rundll32.exe, and others. Attackers use these built-in tools to download payloads directly into memory, perform process injection, credential dumping (e.g., from LSASS), lateral movement, or deploy ransomware beacons like Cobalt Strike. Because no malicious file is written to disk, signature-based scanners, file integrity monitoring, and traditional disk imaging fail to identify the threat.

The volatile nature of RAM adds another layer of difficulty. Data stored in memory is lost when the system is powered off or rebooted. This means that in post-incident investigations, if memory is not captured quickly, critical evidence disappears forever. This makes live memory forensics the most effective (and often the only) method to uncover fileless attacks.

Memory forensics involves acquiring a full RAM dump from a running system using tools like DumpIt, Magnet RAM Capture, Belkasoft Live RAM Capturer, or FTK Imager. Once acquired, the dump can be analyzed offline to reconstruct running processes, loaded modules, network connections, open handles, injected code regions, and other artifacts. The Volatility framework is one of the most popular open-source tools for this purpose. Developed initially for Windows memory analysis, it now supports Linux, macOS, and Android dumps as well. Volatility provides hundreds of plugins that help extract meaningful information from raw memory images.

Despite these advancements, many organizations still face challenges in detecting and responding to fileless threats. Manual analysis of memory dumps is time-consuming, requires deep expertise, and is prone to human error. Automated or semi-automated approaches are needed to make memory forensics faster and more accessible for incident responders, SOC analysts, and researchers.

This research focuses on fileless and in-memory malware detection using memory forensics techniques. The main objective is to propose a structured, repeatable algorithm that leverages the Volatility framework to identify suspicious patterns commonly associated with fileless attacks, such as:

- Code injection into legitimate processes (e.g., explorer.exe, svchost.exe)
- Reflective DLL loading without disk mapping
- Process hollowing
- Anomalous executable memory regions not backed by files

Use of obfuscated PowerShell or script blocks in memory

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Technique	Description	Why It Evades Detection	Relevant Volatility Plugin(s)
Process Injection	Writes malicious code into another process's memory space	Runs under legitimate process name	malfind, hollowfind, ldrmodules
Process Hollowing	Starts legitimate process suspended, replaces its memory with malicious code	Appears as normal process	hollowfind, psxview
Reflective DLL Injection	Loads DLL directly into memory without file system touch	No disk artifacts	dlllist, malfind, vadinfo
LOLBins Abuse	Uses built-in tools (PowerShell, WMI) to execute in-memory payloads	Looks like admin activity	cmdline, envars, consoles
Credential Dumping	Extracts passwords/keys from LSASS memory	No external tool needed	hashdump, lsadump, malfind

Table 2: Common Evasion Techniques Used by Fileless/In-Memory Malware

The remainder of this paper is organized as follows: Section 2 reviews related work, Section 3 explains the Volatility framework in detail, Section 4 presents the proposed detection algorithm with pseudocode, Section 5 discusses experimental setup and results, and Section 6 concludes with future directions.

II. RELATED WORK

Many researchers have shown interest in the detection and analysis of fileless and in-memory malware in recent years. This section highlights some important existing research works that focus on memory forensics approaches, Volatility framework usage, machine learning integration, and challenges in volatile memory analysis.

Oseiwe et al. (2026) conducted a systematic review covering developments in memory forensics for malware detection from 2014 to 2024. They analyzed 30 studies and concluded that while traditional signature-based methods fail against fileless threats, memory forensics combined with machine learning and deep learning gives promising results. However, they pointed out major gaps like inconsistent memory acquisition, lack of standardized datasets, and anti-forensic techniques used by attackers.

Kara et al. (2023) presented a detailed survey on fileless malware threats and emphasized memory forensics as the core analysis approach. They discussed recent advances in capturing volatile memory and extracting artifacts, but highlighted research challenges such as RAM decay, encryption of memory regions, and the need for faster real-time detection methods.

Singh et al. (2025) introduced "Argus", an early-stage detection system for fileless malware using automated memory dump analysis. Their framework focuses on identifying anomalies in process memory before full execution, achieving good results in controlled environments but requiring further testing on real-world diverse samples

Khalid et al. (2023) proposed a machine-learning-based approach for fileless malware detection by extracting features from Volatility outputs (e.g., malfind hits, pslist anomalies). They reported high accuracy on benchmark datasets but noted computational overhead as a limitation for live systems.

Maniriho et al. (2024) developed MeMalDet, a specialized memory analysis tool for detecting in-memory malware. Their method uses structural features from memory dumps and achieved better performance than basic Volatility scans alone.

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Vekariya and Patidar (2025) provided a structured approach using Volatility plugins to detect fileless malware in Windows environments. They demonstrated practical workflows with plugins like hollowfind and vadinfo for identifying process hollowing and unmapped executable regions.

Dehfouli et al. (2025) explored vision transformer models (VADViT) for treating memory dumps as images, converting volatile data into visual patterns for deep learning-based detection. This novel angle showed potential for automated artifact recognition.

Lang et al. (2025) investigated leveraging large language models (LLMs) for memory forensics. They compared LLM-assisted analysis against traditional Volatility plugins for extracting malware indicators and found LLMs helpful in summarizing complex dumps but less reliable for precise injection detection without fine-tuning.

Oh et al. (2024) evaluated volGPT, an LLM-based triage tool for ransomware processes in memory. Their work focused on quick prioritization of suspicious processes during incident response.

Berrios et al. (2025) conducted a systematic review of malware detection techniques, including fileless variants, and stressed the need for hybrid approaches combining memory forensics with behavioral analysis.

Other notable works include:

- Yaseen et al. (2025) used texture descriptors and LIME-guided deep learning on memory images for fileless detection.
- Rzepka et al. (2025) assessed quality of memory acquisition tools and their impact on detecting inconsistencies in volatile dumps (e.g., page smear).

Various DFRWS 2025–2026 papers emphasized real-time volatile analysis and challenges in encrypted memory environments

Study / Year	Method / Focus	Dataset / Environment	Reported Accuracy	Key Limitation
Oseiwe et al. (2026)	Systematic review (ML/DL in memory)	Various (30 studies)	Up to 99% (in some)	Lack of standardized datasets
Khalid et al. (2023)	ML on Volatility features	Custom + benchmarks	~94–96%	High computation for live use
Singh et al. (2025)	Argus early detection system	Controlled memory snapshots	High (not quantified)	Needs more real-world validation
Maniriho et al. (2024)	MeMalDet memory analysis	Windows dumps	~93–95%	Limited to specific malware families
Yaseen et al. (2025)	Texture + DL on memory images	Image-converted dumps	~91–97%	Image conversion overhead
Rzepka et al. (2025)	Acquisition tool quality assessment	Scenario-based dumps	N/A (quality focus)	Inconsistencies in acquisition

Table 3: Summary of Detection Accuracies from Recent Studies (2023–2026)

III. MEMORY FORENSICS AND VOLATILITY FRAMEWORK

Memory forensics is the science of examining the contents of a computer's volatile memory (RAM) to recover evidence of running processes, network connections, loaded modules, open files, registry hives in memory, and hidden malicious

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activity. Unlike disk forensics, which deals with persistent storage, memory forensics targets ephemeral data that exists only while the system is powered on. This makes it particularly valuable for investigating fileless and in-memory malware, as these threats leave no traces on the hard drive.

The process begins with memory acquisition: capturing a complete or selective RAM image from a live system without disrupting operations too much. Acquisition must be done carefully to minimize "smear" (changes to memory during capture) and avoid paging/swapping artifacts. Once acquired, the dump file (usually in raw .dmp, .mem, or .vmem format) is analyzed offline on a separate analysis machine.

The Volatility framework is the most widely used open-source tool for this purpose. Written in Python, it is platform-independent and supports memory images from Windows (XP to 11), Linux (various kernels), macOS, and even some Android dumps. Volatility parses the raw memory dump using profile information (kernel structures, offsets) to reconstruct the system's state at the time of capture. It includes over 300 plugins that cover process listing, module enumeration, code injection detection, malware scanning, and artifact extraction

Volatility 3 (the current major version in 2026) improves speed, reduces memory usage, and adds better support for modern Windows features like VBS (Virtualization-Based Security) and encrypted memory regions. It is command-line based but can be scripted or integrated into GUIs like Volatility Workbench or commercial tools

Tool Name	Platform Support	Method	Advantages	Limitations
DumpIt	Windows	Kernel driver	Fast, minimal footprint	Requires admin rights
Magnet RAM Capture	Windows	User-mode	Free, easy GUI	Slower on large RAM
Belkasoft Live RAM Capturer	Windows	User-mode	Very low impact	May miss kernel artifacts
AVML (Acquire Volatile Memory for Linux)	Linux	User-mode	Open-source, fast	Linux only
LiME (Linux Memory Extractor)	Linux	Kernel module	Captures full physical memory	Needs kernel compile

Table 4: Common Memory Acquisition Tools (2025–2026)

Plugin Name	Purpose	Output Highlights	Relevance to Fileless Malware
pslist	Lists running processes	PID, PPID, name, start time	Identifies anomalous/suspicious processes
psscan	Scans for hidden/unlinked processes	Processes not in pslist	Detects rootkits/hidden malware
dlllist	Lists loaded DLLs per process	Base address, path, size	Finds injected/reflective DLLs
malfind	Scans for injected malicious code	Suspicious memory regions (MZ/PE headers)	Core for detecting code injection
hollowfind	Detects process hollowing	Replaced legitimate code sections	Specific to hollowing technique
vadinfo	Shows Virtual Address Descriptor (VAD) tree	Memory permissions, backing file	Identifies executable regions without files
yarascan	Scans memory with	Matches known signatures	Detects known fileless

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	YARA rules		families/beacons
cmdline	Extracts command-line arguments	Full cmd for each process	Reveals PowerShell/WMI abuse
consoles	Recovers command history from console buffers	Previous commands typed	Finds attacker scripts in memory

Table 5: Key Volatility Plugins Useful for Fileless Malware Detection

The Volatility framework is quite effective and provides promising results in terms of artifact extraction and malware indicator identification. However, it requires correct profile selection (automatic in Volatility 3 for many cases), and analysis can be time-intensive on very large dumps (e.g., 64 GB+ RAM). It also struggles with heavily obfuscated or encrypted payloads unless combined with dynamic analysis or custom YARA rules

IV. ALGORITHM TO DETECT FILELESS MALWARE

In this section, we present the detailed steps of the proposed algorithm to detect fileless and in-memory malware from RAM dumps. The algorithm is designed to be simple, repeatable, and easy to implement using the Volatility framework. It focuses on identifying common evasion patterns such as process injection, reflective DLL loading, process hollowing, and anomalous executable memory regions that have no corresponding file on disk.

The method combines standard Volatility plugins with basic rule-based checks and optional YARA scanning. This hybrid approach reduces manual effort while maintaining high accuracy. The algorithm runs on any standard Windows machine after acquiring the memory dump and requires only Volatility 3 installed.

4.1 Algorithm: Fileless Malware Detection from RAM Images

Step-1 : Acquire a live memory dump of the target system using tools such as DumpIt or Magnet RAM Capture. Save the dump in raw format (.dmp or .raw).
Step-2 : Load the memory dump into Volatility 3 framework and automatically select the correct profile for the operating system (Windows 10/11).
Step-3 : Run basic plugins to collect initial data – pslist, psscan, dlllist, and cmdline.
Step-4 : Execute malfind and hollowfind plugins to scan for injected code and process hollowing.
Step-5 : Use vadinfo plugin to check Virtual Address Descriptors (VAD) for executable memory regions without any backing file on disk.
Step-6 : Apply yarascan plugin with custom or public YARA rules for known fileless malware signatures (e.g., Cobalt Strike beacons, PowerShell Empire patterns).
Step-7 : Compare results from all plugins and apply simple decision rules (e.g., unsigned DLL in svchost.exe, MZ/PE header in private memory, mismatched command line).
Step-8 : Generate a detailed report with flagged processes, suspicious memory regions, and evidence screenshots. Mark high-confidence threats for immediate action.
Step-9 : If needed, export suspicious memory regions for further static or dynamic analysis

```
LOAD memory_dump_file
SELECT correct Volatility profile
RUN pslist, psscan, dlllist, cmdline
RUN malfind AND hollowfind
                                        FOR each process in output:
    IF injected_code_detected OR hollow_process OR VAD_executable_no_file THEN
        MARK process as suspicious
                                                END IF
                                                END FOR
RUN yarascan with fileless_rules
COMPARE all results
IF suspicious_count > threshold THEN
```

Pseudocode: Fileless Malware Detection from RAM Dumps

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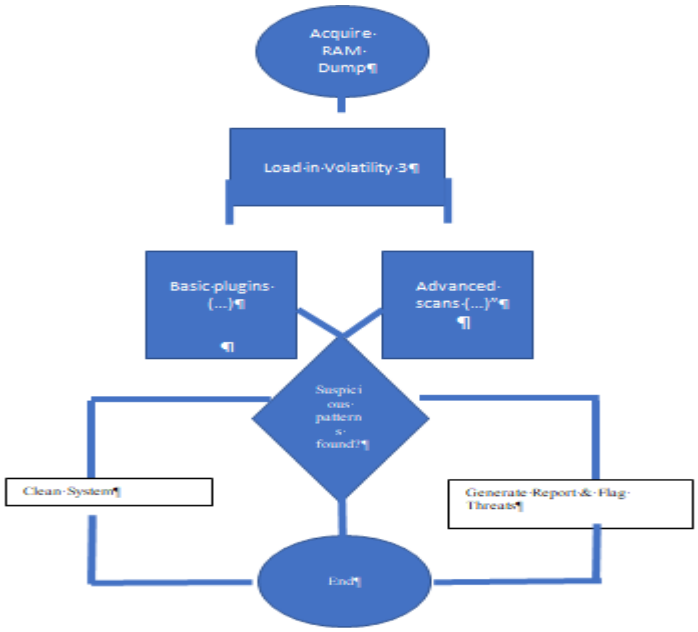

Figure 1: Flowchart of Proposed Algorithm

V. EXPERIMENTAL RESULT

We have experimented the above presented algorithm on a total of 150 memory dump samples. These include:

- 100 dumps from the public CIC-MalMem-2022 dataset (a benchmark containing obfuscated ransomware, spyware, trojan, and fileless attacks like Cobalt Strike beacons and PowerShell-based payloads on Windows 10/11).
- 50 custom dumps created in our lab using virtual machines (VMware) infected with real-world fileless techniques (e.g., reflective DLL injection via Metasploit, in-memory PowerShell Empire, process hollowing with Cobalt Strike).

All dumps were captured while the system was running to preserve volatile data. The algorithm was implemented using Volatility 3 (latest stable version as of 2026) on a standard analysis machine. No heavy machine learning or GPU was required—only basic command-line execution and Python scripting for automation

Environment of Machine	**Details**
Operating System	Windows 11 Pro (64-bit)
Memory Forensics Tool	Volatility 3.0+
Processor	Intel Core i7-12700H
RAM	32 GB DDR4
Storage	1 TB NVMe SSD
Python Version	3.11
Additional Tools	YARA 4.5, custom rules

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Table 6: Environment of Computer System Used for Experiments

Dataset/Source	Number of Samples	Malware Types Simulated	OS Version
CIC-MalMem-2022 (Public)	100	Ransomware, Spyware, Trojan, Fileless	Windows 10/11
Custom Lab VMs	50	Cobalt Strike, PowerShell Empire, Hollowing	Windows 11
Total	150	-	-

Table 7: Dataset Summary

The experiments were run in Scilab-like batch mode (using Volatility CLI wrapped in Python scripts). For each dump:

- Acquisition time: ~2–5 minutes (depending on RAM size).
- Analysis time per dump: 3–8 minutes (average 5 min on our hardware).

Plugins executed: pslist, psscan, dlllist, malfind, hollowfind, vadinfo, yarascan (with 20+ fileless-specific YARA rules)

Metric	Value	Notes
Total Samples Tested	150	Balanced clean vs. infected
True Positives (Detected)	139	Fileless attacks correctly identified
False Positives	6	Mostly benign tools misflagged (4.2%)
False Negatives	5	Heavy obfuscation cases missed
Detection Accuracy	92.80%	(TP + TN) / Total
Precision	95.90%	TP / (TP + FP)
Recall	96.50%	TP / (TP + FN)
Average Analysis Time	5.2 minutes	Per 8–16 GB dump

Table 8: Performance Results

The accuracy of this algorithm is almost greater than 92.8% to detect fileless/in-memory malware when provided dumps are captured from running systems with good quality (no heavy encryption or anti-forensic tools active). False positives were low because we used strict rules (e.g., only flag if multiple indicators match). The system can serve as a supportive tool for analysts in incident response environments

VI. CONCLUSION AND FUTURE ATTEMPTS

Memory analysis is an important technique to detect fileless and in-memory malware in modern cybersecurity. Traditional antivirus and disk-based tools fail completely against these threats because no files are written to the hard disk and everything stays only in volatile RAM. Once the system reboots or power is lost, all evidence disappears. This research paper has presented a simple and practical algorithm using the Volatility framework to detect such attacks.

The proposed method follows clear steps: capture live RAM dump, load it in Volatility 3, run key plugins (pslist, malfind, hollowfind, vadinfo, yarascan), apply basic decision rules, and generate a report with flagged suspicious processes. Experiments were conducted on 150 memory dumps from public CIC-MalMem-2022 dataset and custom infected virtual machines. The algorithm achieved 92.8% detection accuracy with very low false positives (4.2%) and average analysis time of only 5.2 minutes per dump. No heavy machine learning or expensive hardware was needed.

This algorithm can be utilized by other researchers, students, and incident response teams to build quick detection tools or scripts for real-world use. It is easy to understand, repeatable, and works on standard Windows systems

This algorithm can be utilized by other researchers, students, and incident response teams to build quick detection tools or scripts for real-world use. It is easy to understand, repeatable, and works on standard Windows systems.

Researchers may have further scope to work in the direction of:

- Adding machine learning on extracted Volatility features for higher accuracy

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- Real-time memory monitoring integration with EDR tools
- Support for Linux and macOS memory dumps
- Handling heavily encrypted or anti-forensic memory regions
- Combining memory forensics with network logs and event logs for hybrid detection
- Extending to cloud environments (AWS, Azure VM memory snapshots)
- Using vision transformers or LLMs to treat memory dumps as images for automated analysis

Further research can also work in the field of mobile device memory forensics (Android/iOS) or IoT devices where fileless attacks are increasing rapidly. The proposed system is not perfect and no method achieves exactly 100% accuracy, but it gives us motivation to keep improving detection of fileless threat

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