



## Malware in the Telecom Industry: Malware Threats on Mobile Devices, Servers, and 5G Infrastructure

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## Malware in the Telecom Industry: Handheld Devices, Servers, and 5G Infrastructure



- Advanced Persistent Threats (APTs) increasingly target telecom for sensitive data exploitation.
  - Mobile devices
  - Servers
  - Switches
  - 5G Virtualized Infrastructure
- Effect: data breaches, service disruptions, espionage, and financial losses.



#### Malware Types on Handheld Devices and Their Impact



- Mobile devices are prime targets due to the sensitive data they handle, such as personal information, financial details, and authentication credentials
- Impact on Mobile Devices:
  - Loss of personal data.
  - Unauthorized control over the device.
  - Financial and reputational damage.



Common types of malware that attack mobile phones

# Threat Intelligence Report 2023: Identifying attack trends to protect telecom networks and customers'



Monthly mobile network malware infection rates, January 2019 – January 2023





## Malware Affecting Servers and 5G Infrastructure

NOTE OF TECHNOL

- Malware on Telecom Servers (Windows & Linux):
  - Telecom servers running Windows and Linux
  - These servers manage essential operations,
    - to disrupt services or steal sensitive data
- Some popular attacks are:
  - RATs (Remote Access Trojans)
  - Rootkits
  - Crypto-Miners
  - Fileless Malware
  - Ransomware on Servers

- Malware in 5G Infrastructure:
  - virtualized network functions (VNFs)
  - software-defined infrastructure
- Some popular attacks are
  - Firmware-level Attacks
  - Attacks on VNFs
  - Man-in-the-Middle Attacks



## Legitimate Programs Acting Like Malware



- Blurred Lines between Legitimate Apps and Malware
  - Some legitimate apps
    - requesting excessive permissions
    - secretly communicating with external servers
  - $\circ$  Grayware
    - Not fully malicious but engage in ad fraud, data harvesting, or resource abuse
- Challenges in Detection
  - legitimate app crosses the line into behavior similar to malware
  - Must balance between detecting truly malicious activities and identifying overreaching applications.



- Signature-based Malware Detection
- AI/ML Based Malware Detection
- C3iHub Malware Analysis Framework
- Ransomware Detection
- APT Malware and Attribution





There are two approaches for malware detection –

- Signature based detection approach
  - used by traditional AV engines
- Machine learning based detection approach



Signature Based Approach	Machine Learning Based Approach			
Sequence of bytes that can uniquely identify a	Extract characteristics/behavioural features			
binary, e.g.	Train a binary (or multi-class) classifier			
<ul> <li>E.g., Hash (e.g. md5 sum of binary)</li> </ul>	Ways to extract features			
Efficient	Statically			
Easy to evade using polymorphism and	Without executing binaries			
metamorphism	Features: Opcode sequences, byte			
Polymorphism	sequences, ASCII strings, imported API			
Re-encrypt malware code with different	calls, function call graphs			
random encryption key	Dynamically			
Metamorphism	<ul> <li>Execute binary to get behavioral</li> </ul>			
<ul> <li>Register renaming</li> </ul>	features			
Code permutation	Features: dynamic instruction traces,			
<ul> <li>Garbage code insertion</li> </ul>	API call sequences.			
	Certainly, an upgrade over signatures			





- Static signature-based analysis has several shortcomings:
  - Inability to detect previously unknown threats (Zero-Day Attacks)
  - Limited to known patterns
  - High false negatives
  - Ineffective against Polymorphic and Metamorphic malware
  - Slow response to new threats
  - Inability to detect behavior-based anomalies
  - Resource-intensive signature database maintenance





- YARA and Sigma rule-based
  - Structure and creation of YARA rules
    - YARA rules define custom conditions
      - presence of certain strings, binary sequences, or patterns.
    - Components
      - 。 Rule name
      - Meta section
      - Strings section
      - $_{\circ}$  Condition section



YARA rule for a Trojan detection

```
rule Trojan_Generic
 meta:
    description = "Detects generic trojan behavior based on common strings
and patterns"
    author = "DET"
   date = "2024-09-09"
   malware type = "Trojan"
  strings:
    $cmd1 = "GetPassword"
    $cmd2 = "send data"
    $cmd3 = "connect back"
    $url1 = "http://malicioussite.com"
    $ip1 = "192.168.1.100" // Known malicious IP
  condition:
    any of ($cmd1, $cmd2, $cmd3, $url1, $ip1)
```





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#### YARA rule for a ransomware detection

```
rule Ransomware_Generic
  meta:
    description = "Detects generic ransomware behavior based on ransom
notes and extensions"
    author = "DET"
    date = "2024-09-09"
    malware_type = "Ransomware"
  strings:
    $ransom note = "Your files have been encrypted"
    $contact_email = "contact_us@ransom.com"
    $ext1 = ".locked"
    $ext2 = ".crypt"
    $ext3 = ".encrypted"
  condition:
    any of ($ransom_note, $contact_email) or
    for any of ($ext1, $ext2, $ext3) : (ext)
```





Precision and Accuracy of YARA rule detection:

- Strengths:
  - High precision when detecting known malware
  - Flexibility in defining complex conditions
- Limitations:
  - False Positives: If the rule is too generic (e.g., looking for common strings)
  - False Negatives: Polymorphic or obfuscated malware
  - Static: YARA mainly works for static analysis
    - it's less effective against fileless or runtime malware that doesn't leave static signatures.





- Sigma Rules
  - for log-based detection in SIEM.
  - universal format for defining searches and detections based on logs
  - platform-agnostic approach to threat detection.
  - written in YAML format
  - easily translated into the specific query language of SIEM platforms
- Rule Syntax Components:
  - Title/Description
  - Log Source
  - Detection
  - Condition





#### **Example of a Sigma rule:**

flags logs indicating a suspicious process creation where cmd.exe is spawned by explorer.exe title: Detect Suspicious Process Creation
description: Detects the creation of
suspicious processes in Windows
logsource:
 category: process\_creation
 product: windows
detection:
 selection:
 ParentImage: "\*\\explorer.exe"
 Image: "\*\\cmd.exe"
 condition: selection

level: high





- Precision and Accuracy:
  - Strengths:
    - Platform-Agnostic: can be translated into different SIEM queries
    - High accuracy for specific log patterns
    - Ease of Management: Sigma rules are easier to create and update
  - Limitations:
    - False Positives: if too generic
    - Limited Visibility: may miss malicious activity that does not generate detectable log Dependent on Logging Quality: dependent on the quality and completeness of log data.





Limitations of YARA rules

• Static Analysis –

**Challenge**: ineffective against fileless malware and malware which does not unfold malicious intent until execution

- Signature Reliance:
   Challenge: obfuscation, encryption, or polymorphism
- Frequent Rule Maintenance:
   Challenge: need to be constantly updated and refined
- Limited to Files and Memory Dumps:
   Challenge: YARA operates on files, binaries, and memory dumps





Limitations of Sigma rules

- Dependent on Logging Quality
   Challenge: If logging is misconfigured or important events are not logged
- Limited Context
   Challenge: Without full context, false positives
- Manual Rule Tuning Required: Challenge: Different systems and applications generate different types of logs
- No Detection of Fileless Malware:
   Challenge: Not effective for fileless malware that leaves little or no trace in logs







### C3i Malware Analysis Framework

- **Dynamic Malware Analysis: executing** the malware in a controlled environment (sandbox)
  - real-time interactions (file modifications, registry changes, network communications).
  - polymorphic malware, which changes its code upon each execution.
- Hybrid Malware Analysis : Combines static and dynamic analysis
  - Uses static analysis to examine malware without execution, followed by dynamic analysis to observe its runtime behavior.
  - More accurate results.





### C3i Malware Analysis Framework



• Application of AI/ML for Malware Detection



#### Approaches:

- Supervised Learning
- Unsupervised Learning

#### Advantages:

- Can detect previously unseen (zero-day) malware.
- Scalable for large networks and systems.

#### **Challenges:**

- May take longer to classify threats in real-time
- Large datasets and model training
- Malicious File Detection Method using Machine Learning and Interworking with MITRE ATT&CK Framework
- New Trends in AI and Machine Learning for Anomaly Detection, by Dr. Yosef Yehuda





#### A Comprehensive API Call Analysis for Detecting Windows-Based Ransomware

- As a ransomware attempts to encrypt and write the encrypted information into a file, it frequently invokes the API calls "NtReadFile" and "NtWriteFile".
- We identified the important API calls for ransomware detection
  - We pin down a list of 135 API calls from the dynamic analysis for robust classifiers for detecting modernday ransomware strains.





SNo	API Call	Meaning		
1	NtWriteFile	The data is written to an open file using this method.		
2	SetFilePointer	SetFilePointer moves the file pointer in an open file to a new location. Relative to the beginning of the file, the current file pointer position, or the end of the file. The pointer can be moved forwards or backwards.		
3	Process32NextW	Retrieves information from a system snapshot about the next process.		
4	NtClose	The NtClose method closes handles on the objects listed below: 1) Device for communication 2) Input from the console 3) Screen buffer on the console 4) File mapping for event files 5)Process 6)Socket 7)Thread etc.		
5	NtReadFile	Data is read from an open file via the NtReadFile routine.		
6	NtAllocateVirtualMemory	This function gives the caller a new space. Its allocation rule is to start from a predetermined high address, discover an address space in the current process that meets the caller's request, and then give the caller the first address of that free space. As a result, if the search is modified from a fixed high address to a random address, the function's address space becomes randomized.		
7	NtCreateFile	Opens an existing file, device, directory, or volume or creates a new file or directory.		

Table: List of Top-7 API calls that invoked more during the ransomware execution





Figure: Ransomware Families - API call Mean Frequencies

- Performed API call analysis on recent ransomware variants to understand various behavioral patterns. This includes
  - Highlight the top five frequently invoked API calls for the modern-day ransomware families such as LockBit2.0, BlackMatter, BlackCat, Hive, Stop, Cerber, Bubuk etc.
  - LockBit memory-based operations, AvosLocker File-based operations





#### Early Detection of Ransomware using Registry and Trap Files

- Pre-encryption behavior a key source of information
- Importance of Windows Registry w.r.t Ransomware detection
  - Recently used programs
  - Persistence establishment activity
  - Backup copy deletion
  - Execution of scripts
  - Inclusion of new class & icon
- Early detection Registry info alone may not guarantee the best results !!
  - Modern variants often scans for files to encrypt while simultaneously engaging in other malicious activities.
  - Trap Files placement of trap files requires a careful and detailed study



Table: List of registry categories commonly targeted by ransomware





Early Detection of Ransomware using Registry and Trap Files

- We propose RTR-Shield for continuously monitoring registry modifications and trap files.
- We highlight common patterns observed in the registry modifications by analyzing 20 ransomware families in their pre-encryption stage.
- We strategically deploy trap files by considering the combination heuristic and non-heuristic (ML based) methods.





#### Early Detection of Ransomware using Registry and Trap Files

- designed to detect and contain while minimizing file loss and false positives.
- Successfully detected all modern ransomware variants, averaging a file loss of 76 out of 14000 files with a latency of 3.15 seconds.
- RTR-Shield swiftly detected the fastest-known variant, LockBit, within 2.7 seconds, causing an average file loss of 106 files.



Comparison of Latency between Registry Monitor Function and File Trap Monitor Function







DEMO





#### Tactics, Techniques, and Procedures (TTPs) of Advanced Persistent Threats (APTs)



Use highly sophisticated TTPs to remain undetected for long periods





#### **Towards Malware-based APT Attribution**



#### Experiment

- Collected total 5,771 samples belongs to 152 APT groups
- Extract TTPs using CAPA <sup>3</sup> and timestamp information



3. https://github.com/mandiant/capa

Working hours vs non-working hours



Architecture of Experimented Approach



#### **Towards Malware-based APT Attribution**



- To transform the timestamps into vectors, we leverage trigonometric functions (sine and cosine) to project cyclical features onto a unit circle where the start and end of the cycle meet.
- Converted extracted TTPs into feature vector using onehot encoding and inverse document frequency (IDF) method



Fig: Cyclical Feature Encoding: Hours of Day



#### **Towards Malware-based APT Attribution**



Model	Precision	Recall	F1-score
LR	65.89	53.51	56.28
DT	68.98	70.63	68.88
KNN	66.88	55.1	56.96
SVM	77.31	55.94	61.47
NB	41.56	32.31	21.93
RF	80.84	74.15	76.55
XGB	73.82	64.74	67.38
LGBM	79.35	70.27	73.43
AdaBoost	69.79	71.75	70.25
Voting	68.71	68.15	67.23

89.50 8<sup>4.08</sup> 80.91 80.8<sup>A</sup> 16.55 14.15 80 60 -Score (%) 05 20 0 Precision Recall F1-Score

Top-1

Тор-2

Top-1 and Top-2 Performance

Performance of implemented models





- Malware is a major threat to all digital sectors Telecom no exception
- Handsets are target for cybercrime malware
- Infrastructure if target for APT groups
- C3iHub@IIT Kanpur has developed AI/ML based Malware Analysis Capabilities