Context-Aware and Class Imbalance Invariant Threat Severity Assessment for Heterogeneous IoT

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SUBMISSION DATE / POSTED DATE

01-11-2021 / 01-11-2021

CITATION

A, Nitish; Hanumanthappa, J.; S.P, Shiva Prakash; Krinkin, Kirill (2021): Context-Aware and Class Imbalance Invariant Threat Severity Assessment for Heterogeneous IoT. TechRxiv. Preprint.
<https://doi.org/10.36227/techrxiv.16912504.v1>

DOI

[10.36227/techrxiv.16912504.v1](https://doi.org/10.36227/techrxiv.16912504.v1)

APPENDIX A
ROOT CAUSE ANALYSIS (RCA) EXPERT KNOWLEDGEBASE

A. Attack Behaviors, Root Causes, and Fault Scores

The tables I through IV provide high-level expert knowledge information about the attacks and corresponding fault scores (FS) that is necessary for correlated threat severity assessment from [1]. We extract the information from the resources [4]-[12] mentioned in [2].

TABLE I
RCA FRAMEWORK FOR DENIAL OF SERVICE (DoS)

Attack	Behavior	Fault	Fault ID	Cause	FS
DoS	Large incoming network traffic from a HetIoT client to a server IP, Disrupted services	Apache web server client requests with many HTTP headers (around 10,000), Server load average ≥ 5 , Out of memory HTTPD daemon (apache2)	D1	Legitimate HTTP request headers ≤ 20	High
		URL requests with frontslashes $>$ threshold (back)	D2	Victim HTTPD process consuming excess CPU time	Moderate
		Spoofed SYN packet, same source and destination IP, TCP-SYN packet through TCP sockets interface (land)	D3	IP packets with same source and destination addresses are not allowed	High
		Flooding email server with messages, Large number of mail messages from or to a user within a short time (mailbomb)	D4	Varied message thresholds on each site	Imminent
		Half-open TCP connections add records to the TCPD server with pending connections, Simultaneous SYN packets from an unreachable host targeted to a machine (neptune)	D5	Vulnerable implementations of TCP/IP due to the data structure size used for storing incoming connections and the timeout value of half-open connections	High
		Receiving oversized IP packets, Systems crashing, freezing, and rebooting, Noting ICMP packet sizes (ping of death)	D6	Flagging ICMP packets $>$ 64000 bytes.	Imminent
		Large number of active connections on a port, Network services forking or allocating new processes for incoming TCP/IP connections (process table)	D7	Completely filling a target machine's process table with multiple instances of network servers, as incoming TCP/IP connections are usually handled by servers running as root	High
		ICMP echo request packets flooded to IP broadcast addresses from remote locations but none originating from the victim machine (smurf)	D8	Amplifying requests with broadcast addresses upto 255 times (upto 255 machines on an ethernet subnet)	High
		Two fragmented IP datagrams, first is a 0 offset fragment with a payload size N , with the $MF = 1$, second is the last fragment ($MF = 0$) with positive offset $> N$ and payload size $< N$ (teardrop)	D9	Vulnerability in older TCP/IP stacks, Poor handling of overlapping IP fragments by IP fragmentation and re-assembly code	Moderate
		Network suffers congestion and slowdown, Spoofed inbound packets appearing to be originating within the subnet, Looping causes traffic transmission between the chargen or echo port of the two machines (udpstorm)	D10	Unauthorized account access, Single spoofed packet capable of creating a loop, Continues until restarting the INETD daemon	Imminent

TABLE II
RCA FRAMEWORK FOR DISTRIBUTED DENIAL OF SERVICE (DDoS)

Attack	Behavior	Fault	Fault ID	Cause	FS
DDoS	Large incoming network traffic from multiple HetIoT clients to a server IP with all IoT devices following specific traffic pattern, Closely grouped and coordinated behavior of bots, Communication with large number of devices, and Varying destination IPs between time windows	Testing specific credentials in specific ports, Downloading specific type of binary code, Exchanging keep-alive messages, Attacks with specific structures, Generating attack traffic with very few random elements, Infecting through TCP (23-2323, 7547) ports, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (mirai)	DD1	Unsecure remote router access from ISP through port 7547, Webcam vulnerabilities allowing access through port 81, UPnP vulnerability in client router, and Webcam zero-day vulnerability allowing password file access	Imminent
		Distributed communication through BitTorrent DHT and IP discovery through uTorrent transport protocols, RC4 message encryption, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (hajime)	DD2	No malicious behavior, Closes potential IoT vulnerabilities, Potential zero-day exploit	Low
		Exploiting SSH service default credentials, misconfigurations, and known vulnerabilities—inflicting PDoS, Defacing server firmware, Erasing files and reconfiguring network parameters, Continuous deployment and poor management of IoT devices, Improper device placements and allowing considerable traffic processing, Minimal interactions, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (busy box)	DD3	Malwares are light-weight and need less resources to execute, Compatible across multiple platforms, Newer botnets are stealthier	High
		Sudden surge in network traffic, Traffic rate is between low-rate and high-rate DDoS, Larger UDP traffic share, Larger packet sizes and inter-packet interval (flash event)	DD4	Legitimate but harmful traffic, Lack of optimal traffic management and resource allocation policies	Moderate
		Disrupting legitimate user connectivity with spoofed or non-spoofed UDP, ICMP, DNS, or VoIP flood (flooding)	DD5	Exhausted network bandwidth of the victim	High
		Sending forged protocol requests to reflectors with victim IP (reflection)	DD6	”	High
		Consuming victim’s resources via TCP SYN flood, TCP SYN-ACK flood, ACK and Push-ACK flood, or RST/FIN flood (protocol exploitation)	DD7	Exploiting vulnerabilities in protocol implementations	Moderate
		Bots generating large or multiple messages for each message, targeted to victim IP (amplification)	DD8	Exploited IP services	Imminent
		Requests from spoofed IP sources—reflection to a large number of reflectors—amplification (smurf)	DD9	Exploited packet IP broadcast feature	Imminent
Application layer DDoS	Disrupting legitimate services by exhausting server resources, Less bandwidth consumption and stealthy operation, and Targeting specific characteristics of applications (application-level ddos)	Generating large volume of small DNS queries with forged IPs (DNS flooding)	DD10	DNS response message size >> DNS query message size	High
		Sending spoofed VoIP packets through SIP, Very high packet rate and very large random or fixed source IP range (VoIP flooding)	DD11	Victim VoIP server distinguishing the proper VoIP connections from the forged ones consumes excess resources, Unchanged source IP in VoIP flooding mimics Normal traffic and is difficult to distinguish	High

	Sessions that contain high-workload (asymmetric)	Session connection request rates from the attackers > legitimate users – HTTP get/post flooding or excessive VERB (session flooding)	DD12	Non-spoofed HTTP get/post flooding attacks, Hard to detect	High
		Variation of HTTP get/post flooding, Employing HTTP-1.1 feature to allow multiple requests within a single HTTP session (request flooding)	DD13	Attacker limiting the session rate of an HTTP attack, Bypass session rate limitation defense mechanisms	High
		Variation of HTTP get/post flood attack, Forming a single packet embedded with multiple requests, Non-sequential requests within a single HTTP session (multiple HTTP get/post flooding)	DD14	Maintaining high loads on the victim server with a low attack packet rate, Attacker nearly invisible to netflow anomaly detection techniques, Bypassing deep packet inspection techniques by carefully selecting the HTTP VERB	Imminent
		Generating requests to lock up database queries – like SQL injections (faulty application)	DD15	Poorly designs or improper integration with databases, Heavy server resource consumption	Moderate
		Partial HTTP requests that continuously and rapidly grow, slowly update, and never close, continues until all available sockets are taken up by these requests (slowloris)	DD16	Attackers' IP are usually not spoofed, Limited resources can affect the server	Moderate
		HTTP connections held up for a long time without raising any alarms, similar to slowloris (fragmentation)	DD17	Non-spoofed bots establish a valid HTTP connection with a web server, Fragmenting legitimate HTTP packets into tiny fragments and sending them as slow as the server time out allows	Low
		Sending complete HTTP header with "content-length" field of the post message body for benign traffic, Sending data to fill the message body at a rate of one byte every two minutes (slowpost)	DD18	Server waits for each message body to be completed while the attack grows rapidly	High
		Slowly reading the response instead of slowly sending the requests, Setting a smaller receive window-size than the target server's send buffer (slowreading)	DD19	TCP protocol maintains open connections even in idle data communication, Attacker forcing the server to keep a large number of connections open	Moderate
Botnet-based DDoS	Controlling the constituent network devices and making them behave abnormally	Stealthy C&C to bot communication via instant messaging – trinity with UDP, TCP SYN, TCP ACK, and TCP NUL floods and kaiten with UDP, TCP, SYN, and PUSH+ACH floods (IRC-based)	DD20	IRC can connect hundreds of clients via multiple servers, Using legitimate IRC ports to send commands to the bots and can easily hide his presence because of the large volume of IRC traffic, making it difficult to track, Easy to access the list of all the available bots instead of maintaining the list locally	High
		Periodically downloading the instructions using web requests with encrypted HTTP (port 80) or HTTPS (port 443) communications without connecting with C&C server (web-based)	DD21	Hide themselves within legitimate HTTP traffic, Configuring and controlling bots through complex encrypted PHP scripts and, Difficult to detect	High

TABLE III
RCA FRAMEWORK FOR RECONNAISSANCE (RECON)

Attack	Behavior	Fault	Fault ID	Cause	FS
Recon	Large incoming network traffic across multiple HetIoT clients from single or multiple external IPs within a specific time window	ICMP echo requests (ip-sweep)	R1	Device replying before a threshold of requests exposes its IP	Moderate
		DNS zone transfer of brute force scanning (mscan)	R2	”	Moderate
		Traffic via TCP/UDP or via only FIN packets or via only SYN packets (nmap)	R3	Client unable to maintain active monitoring state for longer times	High
		DNS, RPC, unsecure NFS mount points, fingerd, ruserd, and bootd vulnerabilities on TCP (70, 80 FTP, Telnet, SMTP, NNTP, and UUCP) and UDP (DNS, 177) ports (saint)	R4	Exposed vulnerabilities in the system	Imminent
		Subset of vulnerability checking in the following order: NFS export, NFS export via portmapper, NIS password file, REXD, TFTP file, Remote shell, X server, Writeable FTP home directory, Sendmail, and FTP (satan)	R5	”	High

TABLE IV
RCA FRAMEWORK FOR INFORMATION THEFT

Attack	Behavior	Fault	Fault ID	Cause	FS
Theft	Stealthy approach to evade detection, Constantly monitoring and interacting with compromised systems, Appearing similar to legitimate traffic	Advanced social engineering techniques, Obfuscated malwares, Backdoor communication with remote C&C via TCP port 443 (injection flaw)	T1	Encrypted traffic – difficult to inspect, Zero-day vulnerability in the Internet Explorer browser	Low
		Remote C&C connection through remote access toolkit – RAT (RSA APT)	T2	Exploiting the RAT functionalities	Moderate
		Emails appearing to be from trusted sources with spoofed URLs and malwares (phishing)	T3	Lack of security awareness among network users, Poor management of information on social networks, Need for effective monitoring	Low
		Variant of phishing, Highly targeted and technically competent, Harder to implement and is effective (spear-phishing)	T4	” Improper access control mechanisms, Unupdated security policies, Need for log analysis, File integrity checking, Registry monitoring, Rootkit detection, IDS, Frequent vulnerability assessments	High
		Exfiltrating data via TCP port 443 (aurora)	T5	Configuring the port to only allow the traffic from its own proxy, Using access-control lists to permit or deny traffic	Moderate

		Tapping the information that goes on the wire online or offline (eavesdropping)	T6	Allowing unencrypted, unauthenticated traffic	Moderate
		Impersonating sender and receiver to each other modifying the traffic in between, Passive or active (man-in-the-middle)	T7	”	Moderate
				No hashing at edge devices	High
		Copying and possibly modifying the data transmitted between two hosts (replay)	T8	No message timestamping and encryption	Low
		Breaking or guessing passwords through trial and error, Resource intensive but effective, Ineffective on online services (brute force)	T9	Poor authentication constraints	High
		Attempting only a targeted list of weak passwords on a limited number of key combinations that has a high success probability (dictionary)	T10	Weak and predictable passwords, Unencrypted database authentications	High
		Originating within the host network (insider)	T11	Devices not monitored for traffic behavior	Moderate
		Capturing user keystrokes through hardware device or software program (keylogger)	T12	Unencrypted keystrokes, No anti-logger programs	Low
		Basic keyloggers to advanced trojans through phishing (script kiddie)	T13	Lack of anti-malware and intrusion detection systems	Moderate
		Exploiting the TCP session between a web server and a browser and stealing the session tokens (session hijacking)	T14	Easy access to HTTP header, Poor cookie management, Lack of encryption	High
		Monitoring and keylogging through social engineering (shoulder surfing)	T15	Predictable information and passwords	High

APPENDIX B
THREAT SEVERITY ASSESSMENT (TSA) EXPERT
KNOWLEDGBASE

This section presents the proposed *RCA* and *TSA* expert knowledge frameworks.

TABLE V
ORDINAL INFERENCE RULES FOR **IMMINENT** THREAT SEVERITY
ASSESSMENT BASED ON TABLE I

FS	EoD	RoP	Severity
Imminent	Imminent	Imminent	Imminent
Imminent	Imminent	High	Imminent
Imminent	Imminent	Moderate	High
Imminent	Imminent	Low	Moderate
Imminent	High	Imminent	Imminent
Imminent	High	High	Imminent
Imminent	High	Moderate	Moderate
Imminent	High	Low	Moderate
Imminent	Moderate	Imminent	Imminent
Imminent	Moderate	High	High
Imminent	Moderate	Moderate	Moderate
Imminent	Moderate	Low	Moderate
Imminent	Low	Imminent	Imminent
Imminent	Low	High	Imminent
Imminent	Low	Moderate	High
Imminent	Low	Low	Moderate

TABLE VI
ORDINAL INFERENCE RULES FOR **HIGH** THREAT SEVERITY ASSESSMENT
BASED ON TABLE I

FS	EoD	RoP	Severity
High	Imminent	Imminent	Imminent
High	Imminent	High	Imminent
High	Imminent	Moderate	Moderate
High	Imminent	Low	Moderate
High	High	Imminent	Imminent
High	High	High	High
High	High	Moderate	Moderate
High	High	Low	Moderate
High	Moderate	Imminent	High
High	Moderate	High	High
High	Moderate	Moderate	Moderate
High	Moderate	Low	Moderate
High	Low	Imminent	Imminent
High	Low	High	High
High	Low	Moderate	High
High	Low	Low	Moderate

TABLE VII
ORDINAL INFERENCE RULES FOR **MODERATE** THREAT SEVERITY
ASSESSMENT BASED ON TABLE I

FS	EoD	RoP	Severity
Moderate	Imminent	Imminent	High
Moderate	Imminent	High	High
Moderate	Imminent	Moderate	Moderate
Moderate	Imminent	Low	Low
Moderate	High	Imminent	High
Moderate	High	High	High
Moderate	High	Moderate	Moderate
Moderate	High	Low	Low
Moderate	Moderate	Imminent	High
Moderate	Moderate	High	High
Moderate	Moderate	Moderate	High
Moderate	Moderate	Low	Low
Moderate	Low	Imminent	High
Moderate	Low	High	High
Moderate	Low	Moderate	Moderate
Moderate	Low	Low	Moderate

TABLE VIII
ORDINAL INFERENCE RULES FOR **LOW** THREAT SEVERITY ASSESSMENT
BASED ON TABLE I

FS	EoD	RoP	Severity
Low	Imminent	Imminent	Moderate
Low	Imminent	High	Moderate
Low	Imminent	Moderate	Low
Low	Imminent	Low	Low
Low	High	Imminent	Moderate
Low	High	High	Moderate
Low	High	Moderate	Low
Low	High	Low	Low
Low	Moderate	Imminent	Moderate
Low	Moderate	High	Moderate
Low	Moderate	Moderate	Low
Low	Moderate	Low	Low
Low	Low	Imminent	Moderate
Low	Low	High	Low
Low	Low	Moderate	Low
Low	Low	Low	Low

APPENDIX C
BETA APPROXIMATION

Theorem C.1 (HetIoT Traffic Behavior Approximation). *The Beta probability distribution, based on the Poisson-Gamma joint probability distribution, better approximates the inbound and outbound HetIoT traffic behavior with spatiotemporal dependencies across multiple subnets.*

Proof. It is evident that a network traffic dataset consists of both continuous and discrete features, and the Poisson distribution can approximate the discrete network features [3].

If d_i where $D = \{d_i\}_{i=1}^M$, $\forall d_i \in \mathbb{R}^N$ is an inbound or outbound network traffic instance, the accumulation of such events over a unit time interval or volume of connections ($z = 1$) within a subnet is a Poisson process $\mathbb{P}$, formulated as follows [3],[10]:

$$\begin{aligned} \mathbb{P}(d; \lambda z) &= e^{-\lambda z} \frac{(\lambda z)^d}{d!} \\ \Rightarrow \mathbb{P}(d; \lambda) &= e^{-\lambda} \frac{\lambda^d}{d!} \end{aligned} \quad (1)$$

However, the inherent memorylessness and disjointedness properties of a Poisson process [10] make it insufficient to approximate the spatiotemporal dependencies of the HetIoT traffic that span across multiple subnets over varied time intervals—necessitating a continuous distribution that can capture the said dependencies together—essentially offering new insights into the attack behaviors.

Since the Gamma distribution $\mathbb{G}$ is a conjugate of the Beta distribution, the Poisson-Gamma joint distribution model can solve the above problem by estimating the Poisson parameter λ to construct a Markov chain for efficient traffic behavior approximation of the spatiotemporal dependencies taken together; this is formulated as follows [3]:

$$\mathbb{G}(\lambda; b_1, b_2) = \frac{1}{\Gamma(b_1)} b_2^{b_1} \lambda^{b_1-1} e^{-b_2 \lambda} \quad (2)$$

where $b_1, b_2 \in \mathbb{R}^M$ are the Gamma distribution parameters and $\Gamma(b_1) = (b_1 - 1)\Gamma(b_1 - 1)$ is the corresponding Gamma function.

For the network traffic dataset $D \in \mathbb{R}^{M \times N}$ the Gamma distribution parameters b_1 and b_2 are defined as follows:

$$b_1 = \frac{[\mathbb{E}(D)]^2}{\mathbb{V}(D)} \quad ; \quad b_2 = \frac{[\mathbb{E}(D)]}{\mathbb{V}(D)}$$

where $\mathbb{E}$ is the expectation and $\mathbb{V}$ is the variance.

The Beta distribution can approximate the Gamma distribution that occurs naturally at appropriate time intervals between Poisson distributed processes [14]. $\square$

We complete the proof of the above theorem through the following lemma based on the work presented in [14].

Lemma C.1.1 (Beta Approximation of Poisson-Gamma Joint Distribution). *A sample Poisson-Gamma joint probability distributed process with parameters a and b of the form*

$$\mathbb{G}(\lambda; b_1, b_2) = \frac{1}{\Gamma(b_1)} b_2^{b_1} \lambda^{b_1-1} e^{-b_2 \lambda}$$

can be approximated from Beta distribution of the form

$$\mathbb{B}(\lambda; b_1, b_2) = \frac{1}{B(b_1, b_2)} \lambda^{b_1-1} (1 - \lambda)^{b_2-1}$$

resulting in,

$$\text{Sample } (\lambda; b_1, b_2) \sim \mathbb{B}(D; c_1, c_2)$$

where c_1 and c_2 are the Beta distribution parameters.

Proof. We formulate the Beta distribution approximation of the Poisson-Gamma joint distribution from equations (12) and (13) as,

$$\mathbb{B}(\lambda; b_1, b_2) = \frac{1}{B(b_1, b_2)} \lambda^{b_1-1} (1 - \lambda)^{b_2-1} \quad (3)$$

where,

$$B(b_1, b_2) = \int_0^1 d^{b_1-1} (1 - d)^{b_2-1} \partial d^* = \frac{\Gamma(b_1)\Gamma(b_2)}{\Gamma(b_1 + b_2)}$$

*Since the conventional derivative term ‘ d ’ represents a dataset sample, we use the term ‘ ∂ ’ in this scenario.

is the corresponding Beta function with the parameters b_1 and b_2 .

Beta distribution can approximate Gamma distribution that occurs naturally at relevant time intervals between Poisson distributed processes.

It follows from [14] that, if $D = \{d_{Mi}\}_{i=1}^N$ is a set of Gamma distributed independent random variables having the parameters b_{1i} and b_2 , then:

$$\sum_{i=1}^N (b_{1i}, b_2) \Rightarrow b_1 = \sum_{i=1}^N b_{1i} \quad ; \quad b_2 = b_2 \quad (4)$$

From equation (15), it can be specified (for $N = 2$) that, we have Gamma parameters (b_{11}, b_2) and (b_{12}, b_2) . Then, the ratio $\frac{d_{M1}}{d_{M1} + d_{M2}}$ is a Beta distribution variate with parameters b_{11} and b_{12} . i.e.,

$$P(d_{M1}, d_{M2}) = \frac{e^{d_{M1} + d_{M2}} d_{M1}^{b_{11}-1} d_{M2}^{b_{12}-1}}{\Gamma(b_{11})\Gamma(b_{12})} \quad (5)$$

Thus, equation (16) has the following distribution [14]:

$$P\left(\frac{d_{M1}}{d_{M1} + d_{M2}}\right) = \int_0^\infty g(x, y) \partial x = \frac{1}{B(b_{11}, b_{12})} y^{b_{11}-1} (1 - y)^{b_{12}-1} \quad (6)$$

where, $B(b_{11}, b_{12})$ is a Beta function having Beta distribution with the parameters b_{11} and b_{12} .

Substituting the terms v by λ , b_{11} by b_1 , and b_{12} by b_2 in equation (17) results in the following equation:

$$P\left(\frac{d_{M1}}{d_{M1} + d_{M2}}\right) = \frac{1}{B(b_1, b_2)} \lambda^{b_1-1} (1 - \lambda)^{b_2-1} = \mathbb{B}(\lambda; b_1, b_2) \quad (7)$$

which is same as equation (14)—the proposed objective.

Therefore, the behavior of the inbound and outbound HetIoT traffic D , which follows Poisson-Gamma joint probability distribution, can be well modeled by approximating the corresponding parameters λ , b_1 , and b_2 by the Beta probability distribution; this process has the following formulation:

$$\text{Sample } (\lambda; b_1, b_2) \sim \mathbb{B}(D; \lambda, b_{11}, b_{12}) \quad (8)$$

where, λ, b_1 , and b_2 are the Poisson-Gamma joint probability distribution parameters, and b_{11} and b_{12} are the Beta distribution parameters. $\square$

APPENDIX D

PERFORMANCE ANALYSIS OF ALGORITHMS

Theorem D.1 (Computational Complexity Analysis of CorrELM Algorithm). *For a network traffic dataset $D \in \mathbb{R}^{M \times N}$ with M samples and N features and the corresponding expert knowledge $E_{RCA} \in \mathbb{R}^{Q \times 6}$ with Q samples and six features, and C target categories, the computational complexity of the CorrELM algorithm is as follows:*

$$\mathcal{T}_{\text{CorrELM}} \rightarrow \mathcal{O}(M(L^2 + Q) + L^3)$$

$$\mathcal{S}_{CorrELM} \rightarrow \mathcal{O}(L^2 + (2L + Q)C)$$

Proof. We base our implementation of the CorrELM algorithm on the work presented in [13], which shows that the worst-case time and space complexities of the ELM algorithm with L hidden layer neurons and C target categories, respectively, are as follows:

$$\mathcal{T}_{ELM} \rightarrow \mathcal{O}(ML^2 + L^3) \quad (a)$$

$$\mathcal{S}_{ELM} \rightarrow \mathcal{O}(L^2 + 2LC) \quad (b)$$

The time complexity of correlating expert knowledge $E_{RCA} \in \mathbb{R}^{Q \times 6}$ reduces linearly to

$$\mathcal{T}_{E_{RCA}} \rightarrow \mathcal{O}(Q) \quad (c)$$

which follows from expression (i) in the following lemma.

The space complexity of correlating expert knowledge E_{RCA} and the corresponding target category C is

$$\mathcal{S}_{E_{RCA}} \rightarrow \mathcal{O}(QC) \quad (d)$$

Since the CorrELM algorithm classifies M data instances by correlating with Q expert knowledge instances of the matching category C , the corresponding time complexity is determined by combining expressions (a) and (c). i.e.,

$$\mathcal{T}_{CorrELM} \rightarrow \mathcal{O}(ML^2 + L^3 + MQ) \quad (e)$$

which follows from *lines 12 and 13 in Algorithm 4* and the following lemma.

Similarly, the space complexity of the CorrELM algorithm from expressions (b) and (d) is as follows:

$$\mathcal{S}_{CorrELM} \rightarrow \mathcal{O}(L^2 + 2LC + QC) \quad (f)$$

Therefore, the computational complexity of the CorrELM algorithm that follows from expressions (e) and (f) is as follows:

$$\mathcal{T}_{CorrELM} \rightarrow \mathcal{O}(M(L^2 + Q) + L^3) \quad (g)$$

$$\mathcal{S}_{CorrELM} \rightarrow \mathcal{O}(L^2 + (2L + Q)C) \quad (h)$$

□

Corollary D.1.1 (Offline Computational Complexity Analysis of CorrELM Algorithm). *During offline training on a sufficiently large dataset, the computational complexity of CorrELM algorithm reduces to that of ELM algorithm. i.e.,*

$$\mathcal{T}_{CorrELM}^o \approx \mathcal{T}_{ELM}$$

$$\mathcal{S}_{CorrELM}^o \approx \mathcal{S}_{ELM}$$

Proof. Let $D = \{d_i, y_i\}_{i=1}^M \in \mathbb{R}^{M \times N}$ be the network traffic dataset and $E_{RCA} = \{k_j, y_j\}_{j=1}^Q \in \mathbb{R}^{Q \times 6}$ be the corresponding expert knowledgebase for a matching attack category C .

For a sufficiently large network traffic dataset, the corresponding expert knowledgebase is comparatively very small—as a large number of the dataset instances refer to a very small set of expert knowledgebase instances with a matching attack category. Hence, we have

$$D_{M \times N} \gg E_{RCA_{Q \times 6}} \quad (j)$$

because $\mathbb{R}^{Q \times 6} \ll \mathbb{R}^{M \times N}$

Typically, a classifier is trained on an entire (unsampled) large sized network traffic dataset in the background offline. Thus Q has negligible effect on the training time complexity. Therefore, from (j), the expression (g) of the preceding theorem becomes,

$$\mathcal{T}_{CorrELM}^o \rightarrow \mathcal{O}(ML^2 + L^3) \quad (k)$$

which is same as expression (a), and the expression (h) becomes,

$$\mathcal{S}_{CorrELM}^o \rightarrow \mathcal{O}(L^2 + 2LC) \quad (l)$$

which is same as expression (b).

Therefore, from expressions (k) and (l), we can conclude that, for a sufficiently large network traffic dataset during offline training,

$$\mathcal{T}_{CorrELM}^o \approx \mathcal{T}_{ELM} \quad (m)$$

$$\mathcal{S}_{CorrELM}^o \approx \mathcal{S}_{ELM} \quad (n)$$

□

Theorem D.2 (Computational Complexity Analysis of Threat Severity Algorithm). *For m correlated attack alerts and Q corresponding expert knowledge inferences, the computational complexity of the Alert Priority algorithm is,*

$$\mathcal{T}_{severity} \rightarrow \mathcal{O}(mQ)$$

$$\mathcal{S}_{severity} \rightarrow \mathcal{O}(QC)$$

Proof. Algorithm 6 determines the matching fault ID, cause and fault score (FS) for m CTP attack alerts and Q corresponding instances in $E_{RCA}(k) \in \mathbb{R}^{Q \times 6}$, beginning with three instructions (which follows from *lines 1-4* in Algorithm 6)

The algorithm continues to find the matching FS in $E_{TSA}(l) \in \mathbb{R}^{27 \times 4}$, resulting in two more instructions each for 27 E_{RCA} entries (following from *lines 5-7*).

Finally, the algorithm returns threat severity for each correlated attack instance.

Thus, the total instruction execution time is as follows:

$$I_{severity} \leftarrow m \times Q(2 + 27 \times 2 + 1) \quad (o)$$

Threat severity assessment from $E_{TSA} \in \mathbb{R}^{27 \times 4}$ has a constant space complexity as the expert knowledge table is invariant of input size. Therefore,

$$\mathcal{S}_{E_{TSA}} \rightarrow \mathcal{O}(1) \quad (p)$$

Since, the space complexity of the Alert Priority algorithm is the combined space complexities of E_{RCA} and E_{TSA} tables, from expressions (d) and (p), we have:

$$\mathcal{S}_{severity} \rightarrow \mathcal{S}_{E_{RCA}} + \mathcal{S}_{E_{TSA}} \quad (q)$$

Therefore, the resultant computational complexity of alert priority algorithm from expressions (o) and (q) is,

$$\mathcal{T}_{severity} \rightarrow \mathcal{O}(mQ) \quad (r)$$

$$\mathcal{S}_{severity} \rightarrow \mathcal{O}(QC) \quad (s)$$

□

APPENDIX E THREAT SEVERITY ASSESSMENT

The following tables provide attack-wise threat assessments based on the RCA tables. Implementing the ELM classifier algorithm resulted in 46 DoS, 565 DDoS, 182 Recon, and 11 Theft false alerts in total from Table XI of the paper. We present 10 random attack-wise alerts and their assessments in the following tables.

TABLE IX
THREAT SEVERITY ASSESSMENT OF CORRELATED DOS ALERTS

Alert	Fault ID	FS	EoD	RoP	Severity
3	D2	Moderate	Low	High	High
7	D1	High	Moderate	High	High
16	D9	Moderate	Imminent	Moderate	Moderate
12	D7	High	Low	Imminent	Imminent
29	D1	High	High	High	High
34	D9	Moderate	Moderate	Imminent	High
37	D10	Imminent	Imminent	Imminent	Imminent
40	D8	High	Moderate	Moderate	Moderate
45	D6	Imminent	Imminent	Moderate	High
46	D2	Moderate	Moderate	High	High

TABLE X
THREAT SEVERITY ASSESSMENT OF CORRELATED DDoS ALERTS

Alert	Fault ID	FS	EoD	RoP	Severity
28	DD6	High	Low	High	High
52	DD12	High	Low	Low	Moderate
56	DD19	Moderate	Moderate	Low	Low
14	DD7	Moderate	High	High	High
74	DD11	High	High	High	High
88	DD15	Moderate	High	Imminent	High
114	DD17	Low	Moderate	Low	Low
150	DD18	High	Moderate	Low	Moderate
200	DD20	High	High	High	High
350	DD21	High	Low	Low	Moderate

TABLE XI
THREAT SEVERITY ASSESSMENT OF CORRELATED RECON ALERTS

Alert	Fault ID	FS	EoD	RoP	Severity
2	R2	Moderate	Moderate	Moderate	High
4	R4	Imminent	Moderate	Low	Moderate
15	R1	Moderate	Moderate	Low	Low
19	R2	Moderate	Low	High	High
26	R3	High	High	High	High
30	R5	High	High	Imminent	Imminent
62	R4	Imminent	High	Imminent	Imminent
91	R1	Moderate	Moderate	Low	Low
101	R3	High	High	High	High
180	R5	High	High	High	High

TABLE XII
THREAT SEVERITY ASSESSMENT OF CORRELATED THEFT ALERTS

Alert	Fault ID	FS	EoD	RoP	Severity
1	T6	Moderate	Low	Low	Moderate
2	T10	High	Moderate	Low	Moderate
3	T11	Moderate	Low	Moderate	Moderate
4	T9	High	Moderate	Moderate	Moderate
5	T3	Low	Low	Low	Low
6	T5	Moderate	Moderate	Low	Low
8	T14	High	Moderate	Low	Moderate
9	T15	High	Low	Low	Moderate
10	T8	Low	High	Low	Low
11	T2	Moderate	Low	Low	Moderate

REFERENCES

- [1] A. Nitish, J. Hanumanthappa, S. P. S. Prakash, and K. Krinkin, "Expert Knowledge Correlated Threat Evaluation of Intrusion Detection System in Heterogeneous IoT," *TechRxiv*. Preprint. 2021. [Online]. Available: <https://doi.org/10.36227/techrxiv.16722784.v1>.
- [2] N. Koroniatis et al, "Towards the development of realistic botnet dataset in the Internet of Things for network forensic analytics: Bot-IoT dataset," *Future Generation Computer Systems*, vol. 100, pp. 779-796, 2019.
- [3] H. Zhang, X. Yu, and P. Ren, "Deep Adversarial Learning in Intrusion Detection: A Data Augmentation Enhanced Framework," [Online]. Available: <https://arxiv.org/pdf/1901.07949.pdf>
- [4] R. Doshi, N. Aphorpe, and N. Feamster, "Machine Learning DDoS Detection for Consumer Internet of Things Devices," *IEEE Symposium on Security and Privacy Workshops*, 2018.
- [5] S. Behal and K. Kumar, "Detection DDoS Attacks and Flash Events using Information Theory Metrics - An Empirical Investigation," *Computer Communications*, 2017.
- [6] C. Koliass et al, "DDoS in the IoT: Mirai and Other Botnets," *Computer*, vol. 50, pp. 80-84, 2017.
- [7] N. Hoque et al, "Network Attacks: Taxonomy, Tools and Systems," *Journal of Network and Computer Applications*, pp. 307-324, 2014.
- [8] A. Jesudoss and N.P. Subramaniam, "A Survey on Authentication Attacks and Countermeasures in a Distributed Environment," *Indian Journal of Computer Science and Engineering (IJCSSE)*, 2014.
- [9] S.T. Zargar et al, "A Survey of Defense Mechanisms Against Distributed Denial of Service (DDoS) Flooding Attacks," *IEEE Communications Surveys & Tutorials*, 2013.
- [10] M.S. Hoque et al, "An Implementation of Intrusion Detection System using Genetic Algorithm," *International Journal of Network Security & Its Applications (IJNSA)*, vol. 4, no. 2, 2012.
- [11] S. Paliwal and R. Gupta, "Denial-of-Service, Probing & Remote to User (R2L) Attack Detection using Genetic Algorithm," *International Journal of Computer Applications*, vol. 60, no. 19, pp. 57-62, 2012.
- [12] C. Tankard, "Persistent threats and how to monitor and deter them," *Network Security*, pp. 16-19, 2011.
- [13] A. Akusok, K-M. Bjork, Y. Miche, and A. Lendasse, "High-Performance Extreme Learning Machines: A Complete Toolbox for Big Data Applications," *IEEE Access*, vol. 3, pp. 1011-1025, 2015.
- [14] E.W. Weisstein, "Gamma Distribution," *Mathworld*, [Online]. Available: <https://mathworld.wolfram.com/GammaDistribution.html>.