Reducing Information Overload: Because Even Security Experts Need to Blink

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ABSTRACT

Computer Emergency Response Teams (CERTs) face increasing challenges processing the growing volume of security-related information. Daily manual analysis of threat reports, security advisories, and vulnerability announcements leads to information overload, contributing to burnout and attrition among security professionals. This work evaluates 196 combinations of clustering algorithms and embedding models across five security-related datasets to identify optimal approaches for automated information consolidation. We demonstrate that clustering can reduce information processing requirements by over 90% while maintaining semantic coherence, with deep clustering achieving homogeneity of 0.88 for security bug report (SBR) and partition-based clustering reaching 0.51 for advisory data. Our solution requires minimal configuration, preserves all data points, and processes new information within five minutes on consumer hardware. The findings suggest that clustering approaches can significantly enhance CERT operational efficiency, potentially saving over 3750 work hours annually per analyst while maintaining analytical integrity. However, complex threat reports require careful parameter tuning to achieve acceptable performance, indicating areas for future optimization. The code is made available at https://github.com/PEASEC/reducing-information-overload.

CCS CONCEPTS
- Computing methodologies → Cluster analysis; Supervised learning; • Security and privacy → Usability in security and privacy.

KEYWORDS
Clustering, Security, Machine Learning, Computer Emergency Response Teams

1 INTRODUCTION

The cybersecurity threat landscape continuously evolves, with attackers deploying increasingly sophisticated tactics while security findings proliferate across multiple channels. Security personnel struggle to process high volumes of textual reports [12], impeding their primary mission of threat identification and infrastructure protection. Despite existing frameworks like the Cyber Threat Intelligence (CTI) cycle [42] and automation methods [18], information processing challenges persist. While CTI – the process of collecting and analyzing security data to derive actionable recommendations – can be aggregated in Threat Intelligence Platforms (TIPs) [35], the diversity of sources and evolving threats creates significant information overload [16].

Computer Emergency Response Teams (CERTs), as organizational security incident coordinators [44], require current threat intelligence for effective response. Studies reveal that 45% of CERT teams process only critical reports due to understaffing [9], while 13% lack capacity for new information and 11% cannot manage existing volumes. Recent research [12, 17] reinforces these challenges, with 47.6% of analysts reporting burnout and 46.6% identifying threat monitoring as their most time-consuming task. For 19.2% of analysts, automating threat alert enrichment through incident correlation represents a critical priority [12]. Kaufhold et al. [17] highlight persistent manual processes in technical information exchange, redundancy checks, and general automation needs, underscoring the urgency for enhanced information processing solutions.

Goal. This research evaluates clustering algorithms’ efficacy in supporting CERT threat information processing. Clustering enables efficient threat analysis by allowing rapid overview of related data points before detailed investigation. We assess various embedding-clustering algorithm combinations against derived requirements, with particular emphasis on threat messages and security advisories from both commercial vendors and security researchers. This investigation addresses our primary research question: Which cluster
algorithm and embedding combination is suitable to reduce CERT personnel’s information overload (RQ)?

Contributions. This work advances current research through two primary contributions: (i) introduction of ThreatReport, a novel labeled threat report corpus (C1) and (ii) a comprehensive performance comparisons of 14 clustering algorithms on the created embeddings across the five diverse datasets (C2).

Outline. The remainder of this paper is structured as follows: Section 2 examines related work and identifies research gaps. Section 3 details our methodology, followed by our comprehensive evaluation results in Section 4. Section 5 discusses findings and limitations, while Section 6 summarizes our contributions.

2 RELATED WORK

We present related work in embeddings, clustering, and evaluation, culminating in the identification of our research gap.

Embeddings. Embedding methods transform data points into vector representations where similarity is preserved through spatial proximity. These range from simple word frequency approaches to sophisticated language models encoding semantic relationships [36, 49]. Document-level encoding presents unique challenges for threat intelligence processing. Traditional approaches include Bag of Words (BoW), which records absolute term frequencies using a global vocabulary, and Term Frequency-Inverse Document Frequency (TF-IDF), which weights terms by their document frequency [49]. Recent approaches use BERT [7], with Sentence-BERT (SBERT) specifically optimized for embedding longer text units [36]. The MTEB benchmark provides comprehensive performance comparisons of differently-sized large language models (LLMs), including clustering efficacy [33].

Clustering. Clustering algorithms group data points based on similarity metrics such as cosine distance or silhouette scores [13, 41, 49]. Traditional methods range from centroid-based K-Means [25] requiring predefined cluster counts to density-based Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [8] supporting arbitrary cluster shapes. Recent research explores deep learning approaches that leverage intermediate representations [20, 21, 27, 28, 30, 37, 46]. In security contexts, clustering facilitates log summarization [10], Android permission analysis [29], and cybersecurity event detection in social media [39] using various techniques from local sensitivity hashing to neural networks. Vulnerability management benefits from clustering through alternative vulnerability classification [2].

Evaluation. Text clustering evaluation employs both internal metrics (assessing compactness and separability without ground truth) [38] and external metrics (requiring labeled data) [49]. Rosenberg and Hirschberg [40] highlight limitations of traditional metrics like purity and entropy, particularly for edge cases. The V-measure framework [40] combines homogeneity (cluster label consistency) and completeness (label distribution) metrics, providing comprehensive clustering quality assessment. Recent frameworks [22] integrate multiple algorithms, datasets, and metrics for systematic evaluation.

| c   | $|c|$ | $\bar{c}$ | $L_c$ | $L_e$ | $L_{e_c}$ | $\#L_e$ |
|-----|----|-------|------|------|---------|--------|
| CySecAlert | 13 306 | 136 | 119 | 6 | 486 | 2 |
| MSE | 3 001 | 284 | 277 | 57 | 686 | 2 |
| ThreatReport | 461 | 4 370 | 3 366 | 7 | 26 853 | 39 |
| SBR | 5 000 | 887 | 458 | 29 | 32 785 | 5 |
| SMS | 5 574 | 80 | 61 | 2 | 910 | 2 |

Table 1: This table outlines the structural information of the datasets $c \in \{\text{CySecAlert, MSE, ThreatReport, SBR, SMS}\}$. $L_c$ is the sequence $\text{len}(d_{p_i})$ in character for all $d_{p_i} \in c$. It shows the size $|L_c|$, the average length $\bar{L_c}$, the median $L_c$, the minimum $L_{e_c}$ and maximum $L_{e_c}$ data point length, and the number of ground truth clusters ($\#L_e$) of $c$.

Research Gap. While existing research addresses clustering of security information, it primarily focuses on short-form content (e.g., social media posts) [39] or traditional embedding methods [19, 39]. No comprehensive evaluation exists, which compares modern embedding-clustering combinations for longer security texts, such as security advisories or threat reports. This gap is particularly significant given the increasing volume and complexity of security documentation requiring efficient processing by CERT personnel.

3 METHODOLOGY

We present the data used in this work and the requirements for document embeddings, clustering algorithms, and evaluation metrics.

3.1 Text Corpora

This study employs multiple datasets to evaluate the selected clustering algorithms across three distinct use cases: (I) effectiveness in processing threat-related short messages and threat reports, (II) performance in handling security bug report (SBR) across diverse products, and (III) comparative analysis on non-security short messages. Exemplar texts from each corpus are presented in Listing 1, while Table 1 provides a comprehensive overview of the datasets’ structural characteristics.

For security-centric analysis, we utilize three primary datasets: CySecAlert [39], Microsoft Exchange (MSE) [5], and ThreatReport (self-labeled). The CySecAlert and MSE datasets comprise security-related short messages extracted from X (formerly Twitter). The ThreatReport dataset encompasses security-related content aggregated from news outlets and security feeds. While the former two datasets are representative for CERT data aggregations in crisis, the third represents data of the daily work of CERTs. In both areas the volume of information increased tremendously in recent years, while understaffing remained on a high level [14]. For product-specific analysis, the SBR dataset contains security-related messages from issue trackers spanning five distinct products [43]. Both use-cases To establish a baseline for general text classification, we incorporate the UCI SMS Spam Collection [1], which features characteristics common to security domain texts, including abbreviations, non-standard nomenclature, and spam content.

The labeling of ThreatReport was done by two researchers in the field of information security. After the first independent labeling
3.2 Operational Requirements for Automated CERT Information Processing

The exponential growth in security-related data requires CERTs to conduct extensive manual analysis daily, leading to significant operational strain [12, 17]. This sustained cognitive load frequently results in professional burnout and potential workforce attrition. The automation of routine analytical tasks presents a critical opportunity for operational improvement, particularly in the identification of duplicate and related information within incoming data streams. Research indicates that security personnel estimate “half of their tasks to all of their tasks could be automated today” [12]. Drawing from multiple empirical studies [4, 12, 17], we establish the following core requirements for an effective CERT clustering system.

R1 Reducing information overload for CERTs: The clustering system must demonstrably reduce the volume of information requiring manual review through effective cluster consolidation. Cluster homogeneity must be maximized through rigorous outlier management. The presence of misclassified data points would significantly compromise cluster integrity and negate the intended benefits of information reduction. Therefore, the system must prioritize classification accuracy over cluster completeness.

R2 Unburden CERTs: The proposed algorithms must operate with minimal configuration requirements, eliminating the need for continuous model adjustment with emerging vulnerabilities or technologies. Model fine-tuning represents a significant operational overhead. While potentially more engaging than routine document review, such tasks divert resources from core responsibilities: threat identification, analysis, and stakeholder communication.

R3 Retention of data: All alerts must remain accessible, regardless of their cluster assignability. The system must preserve outliers during analysis rather than forcing them into inappropriate clusters. Otherwise, important information might be either missed, due to being assigned to an outlier cluster or simply confused personnel if found in wrong clusters. Either case would diminish the benefits of clustering the data due to lost trust in the system. This requirement aligns with information overload reduction by enabling a discrete outlier cluster for manual review, rather than discarding or misclassifying these data points.

R4 Runtime performance: While not the primary optimization target, the system must complete clustering operations on new data and present results within an operationally acceptable timeframe, defined here as several minutes. The system might be run on-demand by CERT personnel in preparation of the daily inbound information review.

3.3 Embeddings, Clustering, and Evaluation

For the embedding process, we evaluate a diverse range of locally deployable LLMs. The selected models span from lightweight architectures with 33.4M parameters (all-MiniLM-L12-v1) to large-scale models with 7.85B parameters (NV-Embed-v2) [6, 15, 23, 29].

Table 2: Overview of the LLMs used in combination with SBERT (sorted alphabetically).

| Huggingface Model ID | Params |
|---------------------|--------|
| Alibaba-NLP/gte-base-en-v1.5 | 137M |
| jxm/cde-small-v1 | 281M |
| markushayer/cysecbert | 110M |
| meta-llama/Llama-3.2-1B | 1.24B |
| meta-llama/Llama-3.2-3B | 3.21B |
| mistralai/Mistral-7B-v0.1 | 7.24B |
| mistralai/Mistral-7B-v0.3 | 7.25B |
| NovaSearch/stella_en_1.5b_v5 | 1.54B |
| NovaSearch/stella_en_400M_v5 | 435M |
| nvidia/NV-Embed-v2 | 7.85B |
| sentence-transformers/all-MiniLM-L12-v1 | 33.4M |
| sentence-transformers/all-mpnet-base-v2 | 109M |
| thenlper/gte-large | 335M |
| sentence-transformers/gtr-t5-xxl | 4.86B |

Listing 1: Example texts from the different evaluation datasets (CySecAlert, MSE, ThreatReport, SBR, and SMS).

of 10 data points, both researchers discussed their labeling process and aligned differences. Afterward, both researchers continued independent on a half dataset each.

"CyberRange: The Open-Source AWS Cyber Range [...]"

(a) Example text for the CySecAlert dataset (use-case I).

"SMBs need to take immediate action on #microsoft #exchange #vulnerabilities [URL] [...]"

(b) Example text for the Microsoft Exchange dataset (use-case I).

"New CacheWarp AMD CPU attack lets hackers gain root in Linux VMs- November 14, 2023- 03:34 PM-2 A new software-based fault injection attack, CacheWarp, can let threat actors hack into AMD SEV-protected [...]"

(c) Example text for the ThreatReport dataset (use-case I).

"SYSCS_UTIL.SYSCS_COMPRESS_TABLE should create statistics if they do not exist. There must be an entry in the SYSSTATISTICS table in order for the cardinality statistics in SYSSTATISTICS to be created with SYSCS_UTIL.SYSCS_COMPRESS_TABLE SYSCS_UTIL.SYSCS_COMPRESS_TABLE should create statistics if they don’t exist. [...]"

(d) Example text for the security bug report dataset (use-case II).

"Auction round 4. The highest bid is now £54. Next maximum bid is £71. To bid, send BIDS e. g. 10 (to bid £10) to 83383. Good luck"

(e) Example text for the SMS dataset (use-case III).
Table 3: Overview of used cluster algorithms, a short explanation, and the used parameters. If no parameter setting is displayed, we use the defaults selected by ClustPy [22].

| Algorithm               | Description                                                                 | Parameters         |
|-------------------------|-----------------------------------------------------------------------------|--------------------|
| **Partition-based Clustering** |                                                                             |                    |
| K-Means [49]            | Divides data into $k$ clusters by minimizing within-cluster variance. Uses centroid-based approach with spherical cluster assumptions. | $n_{\text{cluster}} = 12$ |
| Bruteforce-K-Means      | Bruteforce to find optimal $k \in \left[2, \sqrt{|c|}\right]$ based on resulting silhouette score, where $c$ is the given dataset. |                    |
| SpecialK [11]           | Determining the optimal number of clusters by developing a probabilistic method to assess if clusters originate from a single distribution |                    |
| SkinnyDip [26]          | Noise-robust clustering algorithm designed for datasets with up to 80% noise, using Hartigan’s dip test of unimodality and recursive univariate projection analysis. |                    |
| **Hierarchical Clustering** |                                                                             |                    |
| AgglomerativeClustering [34] | Hierarchical bottom-up clustering merging closest data points, creating cluster hierarchy via dendrogram. | $n_{\text{clusters}} = 12$ |
| **Density-based Clustering** |                                                                             |                    |
| DBSCAN [8]              | Clusters dense regions separated by low-density areas. Robust to outliers, discovers arbitrarily shaped clusters | $\text{eps} = 0.5$ $\text{min\_samples} = 2$ $\text{metric} = \text{precomputed}$ |
| OPTICS [3]              | Advanced density-based clustering handling varying cluster densities. Creates reachability plot for comprehensive structure analysis. | $\text{min\_samples} = 5$ $\text{metric} = \text{precomputed}$ |
| **Deep Clustering**     |                                                                             |                    |
| DKM [30]                | Deep clustering approach that jointly learns data representations and cluster assignments through a continuous reparametrization for k-Means, solely relying on gradient descent. | $n_{\text{cluster}} = 12$ |
| DDC [37]                | Two-stage deep density-based image clustering framework using convolutional autoencoder and t-SNE for low dimensionality and density-based clustering to recognize clusters. |                    |
| DipEncoder [20]         | Coupling the Hartigan’s unsupervised Dip-test with an autoencoder to obtain cluster embeddings. | $n_{\text{cluster}} = 12$ |
| N2D [28]                | Learns autoencoded embedding, uses UMAP for manifold learning, and applies shallow clustering algorithms. | $n_{\text{cluster}} = 12$ |
| DeepECT [27]            | Builds cluster tree in embedding space, which allows selecting the number of clusters afterwards. |                    |
| DEC [46]                | Neural network clustering with iterative representation and cluster refinement. | $n_{\text{cluster}} = 12$ |
| DipDECK [21]            | Advanced deep clustering with disentangled representation approach.          |                    |

24, 31, 32, 36, 47, 48]. We perform all embeddings using sentence-transformers [36] with the models enumerated in Table 2, utilizing computing infrastructure equipped with either NVidia A100 or NVidia H100 GPUs. Initial attempts to process the embeddings on an Apple M4 system with 24 GB memory proved insufficient due to memory constraints.

Our clustering methodology incorporates algorithms from four major categories: partition-based clustering, density-based clustering, hierarchical clustering, and deep clustering [49], selected based on their prevalence, operational characteristics (e.g., arbitrary cluster shape detection, parameter complexity), and MTEB ranking1. We prioritize algorithmic simplicity to assess performance under minimal parameter optimization. This approach aligns with $R_2$, enabling CERTs to focus on core responsibilities without extensive hyperparameter tuning. Table 3 provides a comprehensive overview of the selected clustering algorithms. To evaluate the requirements $R_2$ and $R_4$ regarding operational burden and runtime performance, we conduct clustering experiments on an Apple M4 system with 24 GB memory. This represents a worst-case scenario using consumer hardware, below typical CERT infrastructure capabilities.

1https://huggingface.co/spaces/mteb/leaderboard
The evaluation framework employs exclusively external metrics for two fundamental reasons. First, internal metrics introduce inherent bias when comparing diverse clustering algorithms, as certain algorithms optimize specific internal criteria (e.g., K-Means for silhouette coefficient). Second, intrinsic evaluation metrics assess cluster morphology rather than semantic accuracy relative to ground truth. For CERT applications, semantic cohesion within clusters is paramount to prevent analytical confusion and redundant verification. We adopt the external metrics proposed by Rosenberg and Hirschberg [40]: homogeneity, completeness, and $V$-measure, with primary emphasis on homogeneity. Homogeneity $h \in [0, 1] \subseteq \mathbb{R}$ quantifies intra-cluster uniformity, achieving its maximum of 1 when clusters perfectly align with ground truth [40]. While completeness $c \in [0, 1] \subseteq \mathbb{R}$ measures object distribution across clusters, our focus on precision renders this metric secondary. $V$-measure $V_{\beta} = \frac{(1+\beta)^{hc} - (\beta^{h})^c}{\beta^{h} + c}$ combines these metrics through their harmonic mean, reaching 1 for optimal clustering. We set $\beta = 0$, effectively reducing $V$-measure to homogeneity, prioritizing semantic consistency for CERT operations.

Our comprehensive evaluation encompasses 14 embedding models, 14 clustering algorithms across 5 datasets, measuring 8 distinct metrics while prioritizing homogeneity. Additional captured metrics include: completeness, $V$-measure, silhouette coefficient, Adjusted Rand Index, Calinski-Harabasz index, Davies-Bouldin index, and runtime performance. All metrics represent averages across 5 consecutive iterations, totaling 4,900 distinct experimental configurations.

4 EVALUATION

Our evaluation methodology comprises three primary components. First, we analyze clustering performance across three distinct dataset categories: (i) CTI datasets, (ii) SBRs, and (iii) general short message data (UCI’s SMS dataset). Second, we assess computational efficiency through runtime analysis of both embedding generation and clustering operations. Finally, we correlate these findings with our research questions and established requirements in the subsequent section.

4.1 Clustering Performance

Our analysis encompasses 196 distinct cluster-embedding combinations for each dataset, with results averaged across 5 consecutive executions. Clustering performance exhibits significant variation correlated with ground truth cluster cardinality and dataset dimensionality. Table 4 presents the five highest-performing cluster-embedding combinations per dataset.

Table 4: The CySecAlert dataset demonstrates superior performance with partition-based clustering methodologies. Model capacity shows limited correlation with performance, as evidenced by comparable results between stella_en_400M_v5 (435M parameters) and NV-Embed-v2 (7.5SB parameters). While homogeneity metrics achieve a maximum of 0.61, additional metrics indicate significant cluster overlap. Completeness remains below 0.11, yielding a maximum V-measure of 0.19. Silhouette coefficient, Adjusted Rand Index, and Calinski-Harabasz index collectively indicate suboptimal cluster separation. The optimal configuration generates 12 clusters, achieving a 99.91% reduction in dataset cardinality.

For the MSE dataset, density-based clustering, specifically OPTICS, achieves optimal performance. Homogeneity reaches 0.49, with superior performance from models below 1.24B parameters (Llama-3.2-1B) to 33M parameters. Auxiliary metrics suggest cluster overlap challenges, while achieving 94.80% input reduction.

The ThreatAlert dataset exhibits optimal performance with deep and density-based clustering, achieving maximum homogeneity of 0.34. These results indicate insufficient performance for production deployment, necessitating enhanced fine-tuning procedures. Supplementary metrics corroborate suboptimal clustering performance. Despite achieving 93.41% dimensional reduction, the clustering quality remains inadequate for operational deployment.

Deep clustering demonstrates superior performance on the SBR dataset, with stella models (cf. Table 2) achieving homogeneity exceeding 0.86. This performance suggests that large-scale models like NV-Embed-v2 are not prerequisite for optimal embedding generation. The configuration achieves 99.76% dimensional reduction while maintaining high homogeneity. However, auxiliary metrics indicate persistent cluster overlap challenges, with silhouette coefficients approximating 0.

For the general-purpose SMS dataset, partition-based and deep clustering algorithms paired with NV-Embed-v2 achieve optimal performance. K-Means clustering achieves 99.78% input reduction with exceptional homogeneity exceeding 0.88 across top-five configurations. However, secondary metrics continue to indicate cluster overlap challenges. Fig. 1 depicts the best and worst performing security related datasets. The rest is depicted in the Appendix.

4.2 Runtime Performance

Runtime analysis encompasses both embedding generation and clustering operations, measured in seconds. Both phases demonstrate acceptable computational efficiency (cf. Tables 4 and 6). Embedding generation peaks at 287 s for the CySecAlert dataset, while requiring only 80 s for the SMS dataset. The CySecAlert dataset exhibits minimum embedding time of 14.31 s with mean execution time of 84.15 s. When combined with clustering operations, DipEncoder requires maximum 344.12 s, while K-Means achieves optimal performance in 4.3 s, yielding total pipeline execution under 300 s. Comparable performance characteristics are observed across optimal cluster-embedding combinations: MSE achieves maximal runtime of 235 s (embed + OPTICS), ThreatAlert requires 220 s (embed + DDC), SBR completes in 300 s (embed + DeepECT), and SMS processing concludes in 155 s (embed + DKM).

5 DISCUSSION, LIMITATIONS, AND FUTURE WORK

This research evaluates the efficacy of clustering methods in mitigating information overload for CERT personnel. While our evaluation demonstrates promising results, several aspects warrant detailed discussion and highlight opportunities for future research.

5.1 Discussion

Our research question “Which cluster algorithm and embedding combination is suitable to reduce CERT personnel’s information overload?” can be answered with qualified success. The evaluation demonstrates that no single combination universally excels across
Table 4: Evaluation of the datasets sorted by homogeneity (H) with ranking (#). It shows the used evaluation combination: clustering algorithm (Algorithm), embedding model (Model), and metrics. The columns denote homogeneity (H), completeness (C), V-measure (V-M), Silhouette coefficient (Sil), Adjusted Rand Index (ARI), Calinski-Harabasz index (CH), Davies-Bouldin index (DB), runtime in seconds (t [s]), and number of predicted clusters (#C), respectively. Results are sorted in descending order by homogeneity (↓). After the evaluation we evaluated the ThreatReport dataset with the parameters n_clusters = 60, denoted as ThreatReport-60.

| Algorithm          | Model                  | H   | C   | V-M | Sil  | ARI  | CH | DB    | t [s] | #C |
|--------------------|------------------------|-----|-----|-----|------|------|-----|-------|-------|----|
| **CySecAlert**     |                        |     |     |     |      |      |     |       |       |    |
| 1 K-Means          | NV-Embed-v2            | 0.61| 0.10| 0.17| 0.01| 0.04| 177.35| 5.27  | 2.75| 12.0|
| 2 BruteForceK-Means| NV-Embed-v2            | 0.59| 0.11| 0.19| 0.01| 0.04| 240.24| 5.42  | 1.65| 8.0 |
| 3 K-Means          | stella_en_400M_v5      | 0.55| 0.09| 0.15| 0.02| 0.04| 205.96| 4.82  | 0.84| 12.0|
| 4 K-Means          | stella_en_1.5b_v5      | 0.54| 0.09| 0.15| -0.01|0.03| 212.45| 4.85  | 0.88| 12.0|
| 5 BruteForceK-Means| stella_en_400M_v5      | 0.54| 0.10| 0.17| 0.02| 0.05| 280.10| 4.99  | 0.61| 8.0 |
| **MSE**            |                        |     |     |     |      |      |     |       |       |    |
| 1 OPTICS           | llama-3.2-1b           | 0.49| 0.10| 0.17| 0.26| 0.03| 16.87 | 1.43  | 3.99| 156.0|
| 2 OPTICS           | all-minilm-l12-v2      | 0.48| 0.10| 0.17| 0.24| 0.03| 17.20 | 1.41  | 4.04| 150.0|
| 3 OPTICS           | all-mpnet-base-v2      | 0.45| 0.10| 0.16| 0.21| 0.03| 16.81 | 1.40  | 3.99| 145.0|
| 4 OPTICS           | NV-Embed-v2            | 0.45| 0.10| 0.16| 0.17| 0.02| 13.74 | 1.53  | 4.01| 161.0|
| 5 OPTICS           | gte-base-en-v15        | 0.45| 0.11| 0.17| 0.20| 0.03| 16.53 | 1.39  | 3.96| 135.0|
| **ThreatReport**   |                        |     |     |     |      |      |     |       |       |    |
| 1 DDC              | gte-base-en-v15        | 0.34| 0.30| 0.32| 0.02| 0.03| 6.90  | 2.26  | 2.90| 30.4 |
| 2 DDC              | all-minilm-l12-v2      | 0.33| 0.29| 0.31| -0.01|0.02| 6.88  | 2.08  | 2.54| 34.0 |
| 3 OPTICS           | gte-large              | 0.32| 0.34| 0.33| 0.08| 0.05| 9.28  | 2.16  | 0.10| 23.0 |
| 4 OPTICS           | stella_en_1.5b_v5      | 0.31| 0.36| 0.34| 0.01| 0.06| 7.67  | 2.01  | 0.14| 25.0 |
| 5 OPTICS           | gte-base-en-v15        | 0.31| 0.35| 0.33| 0.08| 0.06| 7.50  | 2.07  | 0.12| 25.0 |
| **ThreatReport-60**|                        |     |     |     |      |      |     |       |       |    |
| 1 AgglomerativeClustering | gte-base-en-v15   | 0.51| 0.33| 0.40| 0.27| 0.02| 9.26  | 1.65  | 0.03| 60   |
| 2 AgglomerativeClustering | all-mpnet-base-v2  | 0.50| 0.33| 0.40| 0.27| 0.02| 10.59 | 1.55  | 0.03| 60   |
| 3 AgglomerativeClustering | stella_en_400M_v5  | 0.50| 0.33| 0.40| 0.28| 0.02| 10.91 | 1.46  | 0.04| 60   |
| 4 N2D              | gte-base-en-v15        | 0.50| 0.32| 0.39| 0.20| 0.01| 7.38  | 1.99  | 2.92| 60   |
| 5 AgglomerativeClustering | gtr-t5-xxl         | 0.50| 0.32| 0.39| 0.26| 0.02| 9.25  | 1.63  | 0.02| 60   |
| **Security bug report** |                      |     |     |     |      |      |     |       |       |    |
| 1 DEC              | stella_en_1.5b_v5      | 0.88| 0.63| 0.74| 0.02| 0.64| 91.20 | 4.94  | 39.66| 12.0|
| 2 DKM              | stella_en_1.5b_v5      | 0.87| 0.62| 0.72| -0.07|0.61| 87.08 | 5.59  | 33.41| 12.0|
| 3 DeepECT          | stella_en_1.5b_v5      | 0.86| 0.47| 0.61| -0.00|0.35| 62.77 | 5.06  | 68.39| 20.0|
| 4 DEC              | stella_en_400M_v5      | 0.86| 0.60| 0.71| 0.02| 0.60| 96.50 | 4.64  | 39.52| 12.0|
| 5 DEC              | gte-base-en-v15        | 0.84| 0.58| 0.68| 0.04| 0.57| 93.44 | 4.97  | 34.88| 12.0|
| **SMS**            |                        |     |     |     |      |      |     |       |       |    |
| 1 K-Means          | NV-Embed-v2            | 0.89| 0.15| 0.25| 0.02| 0.06| 78.78 | 4.73  | 2.42| 12.0|
| 2 DKM              | NV-Embed-v2            | 0.88| 0.46| 0.60| 0.01| 0.76| 38.83 | 5.90  | 64.98| 12.0|
| 3 BruteForceK-Means| NV-Embed-v2            | 0.88| 0.18| 0.29| 0.03| 0.09| 103.05| 4.95  | 1.22| 8.0 |
| 4 DCC              | NV-Embed-v2            | 0.88| 0.24| 0.37| 0.01| 0.27| 77.20 | 4.76  | 53.21| 8.8 |
| 5 DipEncoder       | NV-Embed-v2            | 0.88| 0.14| 0.24| 0.02| 0.05| 71.92 | 5.44  | 159.85| 12.0|
Figure 1: Result of the best and worst performing security related datasets with regard to the mean homogeneity over 5 consecutive runs. Columns show the clustering algorithms and rows the used embeddings. The separated column and row depict the mean over each column and row, respectively. The models and algorithms are sorted by the rows/columns sum (descending), such that the top left shows the highest result, while the bottom right shows the worst.
Table 5: Runtime results using the mean value of a total of 5 iterations for all datasets.

|                         | K-Means | AgglomerativeClustering | OPTICS | BruteForceK-Means | SkinnyDip | DDC | DEC | DeepECT | DipDECK | DipEncoder | DDM | NED | DBSCAN | SpecialK |
|-------------------------|---------|-------------------------|--------|------------------|-----------|-----|-----|---------|---------|------------|-----|------|--------|-----------|
| **CySecAlert** (GT: | Min     | 0.54                    | 8.08   | 302.67           | 0.40      | 0.06| 76.83| 92.82   | 180.59  | 56.18      | 219.19| 78.87| 73.20  | -         |
|                        | Max     | 4.30                    | 80.28  | 313.88           | 2.94      | 0.40| 131.88| 184.92  | 377.33  | 186.90     | 344.12| 174.94| 133.67 | -         |
|                        | Mean    | 1.51                    | 37.04  | 307.16           | 1.09      | 0.18| 95.09| 123.81  | 236.20  | 113.20     | 265.79| 109.43| 92.34  | -         |

|                         | MSE     | Min     | 0.11   | 0.45       | 3.96      | 0.07| 1.05  | 14.40   | 38.47   | 27.49      | 55.66 | 15.43 | 15.07  | 0.07      |
|                        | Max     | 1.26    | 4.02   | 4.25       | 1.05      | 13.16| 28.29 | 41.53   | 58.35   | 37.79      | 67.15 | 23.04 | 19.63  | 0.08      |
|                        | Mean    | 0.45    | 1.80   | 4.03       | 0.32      | 5.42 | 19.39 | 26.34   | 55.90   | 35.69      | 67.15 | 23.04 | 19.63  | 0.08      |

| **ThreatReport** (GT: | Min     | 0.04    | 0.01   | 0.10       | 0.04      | 0.09| 2.54  | 3.42    | 3.68    | 6.90       | 6.02  | 2.53  | 2.73   | 0.00      |
|                        | Max     | 0.32    | 0.15   | 0.20       | 0.21      | 1.31 | 4.78  | 8.15    | 15.24   | 12.07      | 6.50  | 5.94  | 0.00   | -         |
|                        | Mean    | 0.11    | 0.06   | 0.13       | 0.08      | 0.48 | 3.37  | 4.88    | 8.57    | 9.25       | 8.38  | 4.02  | 3.59   | 0.00      |

| **Security bug report** (GT: | Min     | 0.15    | 1.13   | 16.38      | 0.12      | -   | 25.29 | 31.93   | 61.09   | 21.89      | 91.79 | 27.46 | 25.26  | -         |
|                         | Max     | 0.74    | 2.99   | 17.33      | 1.17      | -   | 30.70 | 39.66   | 88.85   | 48.51      | 105.60| 33.83 | 29.55  | -         |
|                         | Mean    | 0.37    | 2.36   | 16.99      | 0.34      | -   | 28.24 | 36.80   | 70.54   | 36.37      | 95.85 | 31.33 | 28.09  | -         |

| **SMS** (GT: | Min     | 0.25    | 1.38   | 140.46     | 0.16      | 0.03| 29.14 | 35.31   | 76.86   | 42.70      | 29.81 | 27.18 | 1.28   | 4.20      |
|                         | Max     | 2.49    | 13.43  | 176.86     | 1.59      | 1.01| 55.41 | 78.64   | 176.91  | 94.06      | 171.19| 73.11 | 58.07  | 21.56     |
|                        | Mean    | 0.92    | 6.70   | 149.56     | 0.69      | 0.34| 39.96 | 54.12   | 112.33  | 64.32      | 46.51 | 40.02 | 1.39   | 13.83     |

Table 6: Tabular display of runtime statistics of embedding the different datasets.

| Dataset                  | Min     | Max     | Mean | Median | Std |
|-------------------------|---------|---------|------|--------|-----|
| CySecAlert              | 14.31   | 287.40  | 84.15| 48.58  | 93.60|
| MSE                     | 5.01    | 230.32  | 51.72| 17.86  | 68.36|
| ThreatReport            | 4.05    | 215.21  | 55.26| 24.90  | 75.88|
| SBR                     | 11.18   | 210.71  | 68.47| 40.83  | 63.69|
| SMS                     | 7.28    | 80.53   | 32.89| 23.86  | 27.44|

Information overload represents a primary factor in CERT personnel burnout and attrition [12]. To address this challenge, we established clustering requirements through comprehensive analysis of current research [4, 9, 12, 17]. Our methodology incorporated both established and novel clustering approaches, leveraging diverse LLMs for document embedding (cf. Tables 2 and 3). The evaluation framework prioritized homogeneity as an external metric [40], analyzing three distinct CTI datasets [5, 39], including our novel ThreatReport dataset (CT), alongside SBR data [45] and the UCI SMS corpus [1].

Our results indicate that achieving homogeneous clustering for CTI advisories and reports presents significant challenges. While CySecAlert and MSE datasets achieve homogeneity scores of 0.61 and 0.49 respectively, these metrics do not fully address primary CERT operational requirements. The ThreatReport dataset achieves only 0.34 homogeneity with default parameters (cf. Table 3), resulting in mixed clusters and complex structures (indicated by near-zero silhouette scores). A subsequent analysis with adjusted parameters (n_clusters = 60 versus default 12) for the all CTI datasets, though several configurations show promising results. For immediate operational deployment, deep clustering combined with stella models achieves optimal performance on SBR data (homogeneity 0.88), while partition-based clustering with NV-Embed-v2 performs well on general security data (CySecAlert, homogeneity 0.61). However, the core CERT focus on threat reports (ThreatReport) requires careful parameter tuning, achieving homogeneity of 0.5 only with adjusted cluster counts.
ThreatReport dataset yields substantially improved results, surpassing 0.5 homogeneity and approaching CySicAlert and MSE performance (cf. ThreatReport-60 in Table 4). This indicates, that the clustering algorithms require further parameter optimizations for the ThreatReport dataset, beyond simple adjustments like setting $n_{clusters}$. The SBR dataset demonstrates exceptional potential with homogeneity exceeding 0.88, though cluster structure remains complex (silhouette scores approximating 0). Deep clustering methodologies effectively address these structural challenges, producing promising results. These findings suggest clustering offers domain-specific utility (e.g., security bug report), while CERT applications may require algorithmic fine-tuning or careful dataset curation. The methodology demonstrates strong generalization, evidenced by SMS dataset homogeneity nearing 0.9.

All evaluated algorithms achieve data reduction exceeding 90%, directly addressing requirement R1 for information overload mitigation. Even with adjusted parameters, the ThreatReport dataset maintains reduction rates above 86.98%, validating clustering efficacy in CERT operations. The simplified configuration aligns with requirement R2, reducing operational burden while preserving original data points R3.

Runtime performance exceeds expectations, with complete processing requiring approximately 5 minutes. This efficiency could potentially save a single CERT over 3750 hours annually. This performance satisfies requirement R4 while preserving operational capacity for core CERT infrastructure security responsibilities.

5.2 Limitations and Future Work

Our methodology exhibits several key limitations. Parameter optimization was intentionally omitted to align with requirement R2; though results suggest its necessity for heterogeneous CTI report processing. Our evaluation methodology is constrained by the limited number of consecutive runs (5), hardware restrictions (Apple M4, 24 GB memory), and consistently poor cluster separation indicated by silhouette scores approximating 0.

Dataset limitations include potential bias in the manually labeled ThreatReport dataset and significant performance sensitivity to cluster count parameters (12 versus 60 clusters). While achieving high dimensional reduction (>90%), the long-term impact of false negatives on CERT operations remains unevaluated. Additionally, we excluded domain-specific features (e.g., CVE identifiers, OWASP classifications) and foundational models (e.g., Claude, DeepSeek, GPT) from our analysis.

Future work should address these limitations through expanded stability analysis, alternative distance metrics, systematic parameter sensitivity evaluation, and integration of domain-specific features while maintaining operational simplicity. The exploration of multilingual capabilities and assessment of false negative impact on operational efficiency present additional research opportunities.

6 Conclusion

This work investigated the application of clustering algorithms for reducing information overload in CERT operations. Through comprehensive evaluation of 196 cluster-embedding combinations across five datasets, we demonstrate that clustering can effectively reduce information processing requirements by over 90% while maintaining semantic coherence. However, optimal performance requires careful selection of clustering approaches based on specific data characteristics.

Deep clustering combined with stella models demonstrates superior performance for structured security data (SBR, homogeneity 0.84), while partition-based clustering with NV-Embed-v2 excels for general advisory content (CySicAlert, homogeneity 0.61). The more complex ThreatReport dataset requires parameter adjustment to achieve acceptable performance (homogeneity 0.5), highlighting the need for domain-specific tuning. Runtime performance remains consistently efficient, with complete processing requiring approximately five minutes, potentially saving CERTs over 3750 hours annually.

While our evaluation demonstrates clustering’s potential for information overload reduction, several challenges remain. Future work should address cluster separation optimization, systematic parameter tuning, and integration of domain-specific features while maintaining operational simplicity. Despite these limitations, our findings suggest that clustering approaches, when properly configured, can significantly enhance CERT operational efficiency without compromising analytical integrity.

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3Respondents stated a daily workload of up to 2 hours [17], which is reduced to 5 minutes and can be run asynchronously plus at most 30 minutes information screening: $250 \times 1.5 \text{ hours} = 3750 \text{ hours}$. 

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APPENDIX

The heatmaps show mean homogeneity scores for embedding-clustering combinations across four datasets. Higher scores (yellow) indicate better clustering: MSE (0.4), CySecAlert (0.6), SMS (0.8), and ThreatReport-60 (0.2–0.5). Marginal means summarize model and algorithm performance.