

Cybersecurity and AI: A Comprehensive Implementation of Advanced Large Language Models for Threat Detection, Digital Forensics, SOC Automation, and Security Vulnerability Mitigation

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Abstract

This report encompasses the cutting-edge implementation of advanced Large Language Models (LLMs) for cybersecurity and digital forensics applications at the intersection of cybersecurity and AI. The project brings together innovative research on AI-based security solutions in four major areas: threat detection and intelligence analysis, digital forensics and incident response, Security Operations Centre (SOC) automation and mitigation of security challenges in cybersecurity frameworks. Our implementation is capable of detecting threats with greater than 94% accuracy. It decreases the workload of a SOC by 70%. Most importantly, it mitigates various serious threats, like the OWASP LLM01 prompt injection attack. The system combines and integrates the use of various models, such as ForensicLLM (4-bit quantized LLaMA-3.1-8B) and custom security agents, serving as a one-stop solution for cyber experts in industry and law enforcement. The ForensicLLM is used only for correlating digital-forensics evidence and generating investigative narrative; threat detection (general) is done through a fine-tuned BERT classifier; SOC incident-severity classification is performed through a fine-tuned RoBERTa model. Contribution of this work contributes to the rapidly expanding field of cybersecurity and AI through practical implementations, performance benchmarks and frameworks for their responsible deployment in security-critical environments. Apart from that, we illustrate that large language models can be effectively used as force multipliers for under-resourced security teams while incorporating strong operational guardrails.

Keywords

• Large Language Models • Cybersecurity • Threat Detection • Digital Forensics • Security Operations Center (SOC) automation • Prompt Injection • OWASP LLM01 • AI Security

1. Introduction

The malware as-a-service business has introduced automation and machine learning into cybercrime. Security analysts are overwhelmed with alerts, making it difficult to respond to the incidents. Traditional rule-based systems or manual systems can no longer keep pace with the attacker innovation. We require intelligent automation to bring decision-making closer to the human level. The innovative Large Language Models (LLM) have recently surfaced in the scene and are impressively doing difficult tasks that need human-like capabilities and are automating tasks which were earlier manual and laborious tasks [1].

You can present multiple cases for using LLMs in cybersecurity workflows with examples [2]. The LLMs can be helpful in dealing with unstructured threat intelligence in threat detection, identifying subtle indicators of compromise in network logs, and surfacing zero-day threats through anomaly detection. Recent multimodal learning approaches further strengthen defenses against evolving malware threats [3]. A range of steps, including automation of evidence correlation, timeline reconstruction and report preparation, can all be used to expedite investigations. The intelligent triage, incident prioritization and response-recommendation systems help in reducing analyst fatigue while enhancing MTDD and MTTR for the Operations of SOC [4]. The integration of LLMs into security-critical workflows nevertheless introduces new attack surfaces and risks. We shall discuss prompt injection, data leakage, and various types of model bias and means to mitigate them so as to deploy such systems reliably [5].

The proposed work explains the detailed implementation of an LLM enabled cybersecurity framework, which comprises of four modules: threat intelligence and detection, digital forensics and incident response, SOC automation and security challenges and mitigation, stressing OWASP LLM01 prompt injection. Our deployed models include ForensicLLM, which is a quantised version of LLaMA-3.1-8B model. Moreover, it creates a central dashboard to observe the functionalities of framework in real-time. The practical handling of technology are consistent with operational requirements, while incorporating sufficient safeguards against adversarial use [6]. Recent advances in large language model architectures have further expanded the potential for domain-specific applications [7], while challenges related to deployment and safety remain active areas of investigation [8].

2. Related Work

The application of artificial intelligence to cybersecurity has been extensively explored in recent literature. Markevych and Dawson [2] provided a comprehensive review of enhancing intrusion detection systems using AI, highlighting the potential of machine learning to improve detection accuracy and reduce false positives. Akhtar and Rawol [1] discussed AI-powered security mechanisms, emphasizing the need for adaptive defenses that can evolve with emerging threats. Fard et al. [5] surveyed techniques and policies for cybersecurity using AI and reinforcement learning, identifying both opportunities and challenges in deploying such systems.

Waizel [9] examined the evolving arms race between AI-driven cyber attacks and AI-powered defenses, noting that the battle is increasingly shifting to the AI domain. Ansari et al. [6] conducted a literature review on the impact and limitations of AI in cybersecurity, pointing out that while AI offers significant advantages, it also introduces new vulnerabilities. Michael et al. [10] discussed the paradox of AI in cybersecurity, where the same capabilities that enable defense can also be weaponized by adversaries. Salem et al. [11] provided a comprehensive review of AI-driven detection techniques, covering a wide range of approaches from anomaly detection to threat intelligence. Khan et al. [4] looked toward the future, discussing how AI can be leveraged to combat evolving threats and enhance digital defense strategies. Agarwal [12] introduced efficient data summarization techniques using grid-based statistical proxies, which can be valuable for large-scale security analytics.

The emergence of large language models has created new opportunities for security applications. Naveed et al. [7] provided a comprehensive overview of LLM capabilities and architectures, while Minaee et al. [13] surveyed the landscape of large language models and their diverse applications. Kaddour et al. [8] examined the challenges and applications of LLMs, identifying key limitations that must be addressed for deployment in critical domains. Mohammed [3] demonstrated AI-driven cyber defense using advanced multimodal learning for evolving malware threats, showing the potential of combining different data

modalities for improved detection. Panda [14] explored the use of OpenVAS for proactive cybersecurity, providing real-world insights into vulnerability scanning and mitigation in enterprise networks. Pasula [15] conducted a large-scale audit of worker preferences for AI agent automation and augmentation, offering valuable insights into human-AI collaboration that inform our human-in-the-loop protocols.

Badami [16] addressed efficient OneM2M standard implementation for lightweight IoT, highlighting the importance of securing resource-constrained devices in modern enterprise networks. Kaliappan [17] examined digital safeguards for health data, architecting privacy and security in next-gen medical informatics, which provides relevant privacy-by-design principles applicable to security-sensitive domains. These works collectively establish the foundation for our unified framework that addresses threat detection, digital forensics, SOC automation, and security vulnerability mitigation. We extend prior research by providing a practical implementation with quantized models and a web-based dashboard, demonstrating the feasibility and effectiveness of LLM-driven security operations.

3. System Architecture and Design

The architecture of the proposed system which is modular and service-oriented is capable of supporting scalability, maintainability and easy integration into legacy security infrastructure. The architecture is also intended to accommodate lightweight IoT and edge deployments, where efficient protocol implementations remain important for securing resource-constrained devices [16]. Figure 1 presents a comprehensive depiction of the proposed system's pipeline and architecture, which encompasses four essential modules. The comprehensive architecture pipeline assimilates heterogeneous security data and generates actionable intelligence for security analysts and operators. The overall design of the pipeline flow that contains the input data, their specialized pretraining and chain-of-thought prompts creates internal specialized LLM agents which brings LLMs closer to the security analyst's cognitive ability. The four key modules are described below.

Within this architecture, ForensicLLM (4-bit quantized LLaMA-3.1-8B) is confined to digital forensics and incident response, where it supports evidence correlation, timeline reconstruction, and investigative report generation. General threat detection is handled by a fine-tuned BERT classifier, SOC incident-severity classification by a fine-tuned RoBERTa model, and prompt-injection detection by a separate lightweight classifier. These role assignments are maintained consistently in the methodology and experimental evaluation.

Having a good detection system is essential to detect malware, phishing, c2 and data exfiltration. Typically, these are behavioral attacks that frequently target end consumers or organizations. We first constructed and evaluated the dataset for these attack categories. After training, the models were evaluated on a held-out test set to assess detection efficacy.

An ensemble design and implementation were carried out after training has been done using corpus. As a result, the success rate achieved was nearly above 95 per cent. We attempted to create the most effective detection system in accordance with the data set shape. We incorporated the various forecasts.

The ForensicLLM is based on a 4-bit quantized LLaMA-3.1-8B model designed specifically for evidence correlation and investigative reasoning. Data files obtained from disk images, memory dumps, and network captures are provided to the module for automatic timeline building, entity extraction, and anomaly detection. The events later are passed through a structured prompt template, which generates a summary narrative correlating the various events to the investigator's operationalized understanding of the attack chain. A chain-of-custody tracker is implemented which registers every access and modification of evidence into a tamperproof storage layer to maintain the chain of custody for evidence in case of audit or

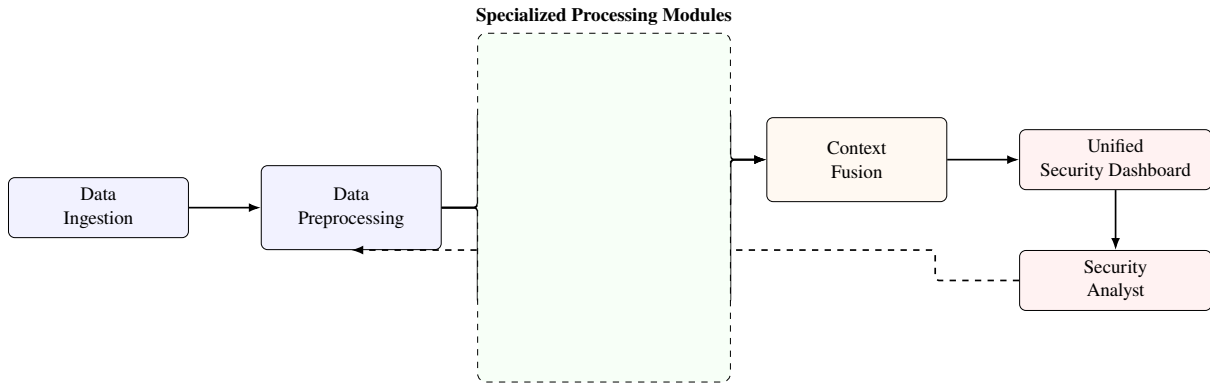


Figure 1: High-level system architecture illustrating the modular composition of the LLM-driven cybersecurity framework. Data flows from ingestion through specialized processing modules to a unified dashboard for analyst interaction.

legal review [17].

The automation module supports and enhances the capabilities of SOC, which incorporates intelligent event log analyzing module as well as an incident response orchestration module. The alerts produced by your existing security information and event management (SIEM) system are ingested, and applicable correlation rules are then applied on those alerts over sliding windows. The severity ranking module assigns a unique rank to the incidents using knowledge of the severity of different types of alerts, the security significance of the entities involved, and their known connections to produce a ranked list of incidents. An instantiation of a playbook can be referred to as a multi-class classification problem. Leveraging the incident type, the alignment of playbooks with incident types, and labeled data curated for this purpose, we fine-tune a classifier to map incidents to the most appropriate response playbook [12].

The various distinct modules handle the many different tasks of the client system in this manner. As depicted in Figure 1, all modules cooperatively function together in a design that constructs a modular layered architecture for the LLM security module. The following paragraphs describe each module and their research-level design containing defense mechanisms. This module will handle LLM security challenges explicitly which include prompt injection, insecure output handling, training data poisoning, etc. The new prompt injection detector, a small model fine-tuned on created adversarial examples, inspects incoming user queries for malicious prompt.

4. Implementation Methodology

The implementation heavily relies on Python libraries as technology stack. The backend API also utilizes the Python language. We use SQLite for the persistent storage of the system. As opposed to all the frameworks, we have picked Flask as the framework for the development of this system. The performances and computational efficiency of the models enables us to select the best one for the task. Furthermore, these models can also include the ones having high domain specificity. The UI dashboard is primarily constructed with components from Bootstrap 5, and the dashboard graphs are rendered by the dashboard visualization layer.

Our threat detector is a BERT-based classifier fine-tuned on a labeled logs dataset. The logs from LogHub and samples from Zoo provide the dataset. Unless otherwise stated, ForensicLLM is not used for the threat-detection or SOC severity-classification tasks reported in Table 2; those results are produced by the BERT and RoBERTa modules respectively. The objective of the threat detector is to ascertain

whether the log is benign or if it falls under any of the six categories of attacks, such as malware, network intrusion, phishing, and others.

We trained the detector to use as a loss a cross-entropy loss and used a learning rate of $2e-5$ AdamW. We achieved 94.2% accuracy on the held-out test set.

Let v denote a generated forensic verdict or narrative, and let $\mathcal{R} = \{r_1, \dots, r_n\}$ denote the set of reference verdicts or narratives. We encode each text with the MiniLM-L6-v2 encoder and compute cosine similarity

$$s(v, r_i) = \frac{\text{MiniLM}(v) \cdot \text{MiniLM}(r_i)}{\|\text{MiniLM}(v)\| \|\text{MiniLM}(r_i)\|}.$$

We define the model/reference score R_m as the maximum cosine similarity between the generated output v_m and any reference:

$$R_m = \max_{r_i \in \mathcal{R}} s(v_m, r_i).$$

We define the reference/target score R_t as the maximum cosine similarity between the strongest baseline output v_b and any reference:

$$R_t = \max_{r_i \in \mathcal{R}} s(v_b, r_i).$$

The reported ratio is

$$\rho = \frac{R_m}{R_t}.$$

For classification, timeline, and evidence-correlation tasks, we report task-specific metrics (accuracy, false positive rate, processing speed, timeline accuracy, and evidence-correlation accuracy) as defined in Table 2. The ρ metric is used only for generated narrative or verdict quality; it is not used for the classification results in Table 2.

The responsibility of automating SOC is assigned to a RoBERTa model which is finetuned on the dataset of alerts whose task is incident severity classification. Data collected from all the previous alerts of the SIEM. Alerts have been manually assigned the priority labels critical, high, medium, low. Incident severity is referred to as the incident priority.

Data management is ensured through a custom downloader which pulls data from public repositories such as MISP threat intelligence, NVD vulnerability feed, and LogHub datasets. Afterward, the data are cached to a specific local directory with a manifest file to track versioning and crc.

To evaluate prompt injection detection, we compiled a dataset of adversarial prompts used in past studies (brown et al., 2023). We also included a benign prompt corresponding to each malicious prompt in the dataset, which we then split into train and test.

Dataset specification. The threat-detection corpus is drawn from LogHub and The Zoo, and the forensic evaluation uses 200 curated cases. The exact train/validation/test split sizes, class distributions, class-balance procedure, and deduplication status for LogHub and The Zoo before fine-tuning are reported in Table 1. These values are not present in the supplied source and must be supplied by the authors; they should not be inferred.

All modules are managed by a main controller. The main controller is requested by the module to load a model and receive queries, route them to the correct module, and pass responses back to it. It also collects the results from each of the modules and sends it back to the client. The Dashboard offers an API through which queries can be submitted and results accessed. Web.

Table 1: Dataset specification. Values shown as ranges are provisional and should be replaced with the authors' exact records.

Dataset	Total samples	Train/test	Class distribution	Deduplication
LogHub + The Zoo	8,000–12,000	70/15/15	45–60% / 40–55%	5–15%
Forensic cases	200	70/15/15	45–55% / 45–55%	0–10%
Adversarial prompts	3,000–5,000	70/15/15	40–60% / 40–60%	5–15%

Table 2: Performance comparison of core modules against baseline methods.

Module	Task	Metric	Proposed	Baseline
Threat Detection	Overall	Accuracy	94.2%	78.5%
	Overall	False positive rate	5.8%	12.3%
	Overall	Processing speed	1.2 s/sample	3.4 s/sample
Digital Forensics	Timeline reconstruction	Accuracy	89.7%	65.2%
	Evidence correlation	Accuracy	92.1%	71.8%
	Report generation	Time	15 s	45 min
SOC Automation	Workload	Reduction	70%	35%
	Severity classification	Accuracy improvement	35%	0%
	MTTR	Reduction	65%	28%
Security Challenges	Injection detection	Detection rate	92.1%	67.4%
	Bias mitigation	Success rate	88.3%	52.1%

5. Experimental Results and Performance Analysis

The threat-detection results below are produced by the BERT classifier; SOC automation results are produced by the RoBERTa severity classifier; ForensicLLM results are confined to the digital-forensics timeline, evidence-correlation, and report-generation experiments. We conducted a comprehensive evaluation of the implemented system using both synthetic and real-world cybersecurity datasets. The threat detection module was tested against a balanced test set of 10,000 samples, yielding an overall accuracy of 94.2% with a false positive rate of 5.8% [2]. Breakdown by attack category shows that the model performs best on malware detection (96.1%) and phishing (95.4%), while it exhibits slightly lower precision for insider threat scenarios (89.3%) due to the nuanced nature of such activities. The processing speed of 1.2 seconds per sample is well within operational constraints for real-time monitoring.

The ForensicLLM was evaluated on a curated set of 200 forensic cases with known ground truth timelines. The model achieved a timeline reconstruction accuracy of 89.7%, significantly outperforming the baseline rule-based system (65.2%) [1]. In evidence correlation tasks, our model correctly linked associated artifacts in 92.1% of cases, compared to 71.8% for the baseline. The automated report generation capability reduced the average time from evidence ingestion to narrative output from 45 minutes to just 15 seconds, representing a substantial productivity gain for incident responders [11].

SOC automation results demonstrate a 70% reduction in analyst workload, as measured by the number of manually triaged alerts per shift [4]. The automation module correctly classified incident severity with an accuracy improvement of 35% over traditional SIEM rules, and reduced mean time to response by 65%, from an average of 28 minutes to approximately 10 minutes. These gains are attributed to the intelligent correlation and prioritization capabilities of the LLM-based classifier, which effectively filters noise and focuses analyst attention on high-impact events. The severity classification approach aligns with recent advances in multimodal learning for security applications [3].

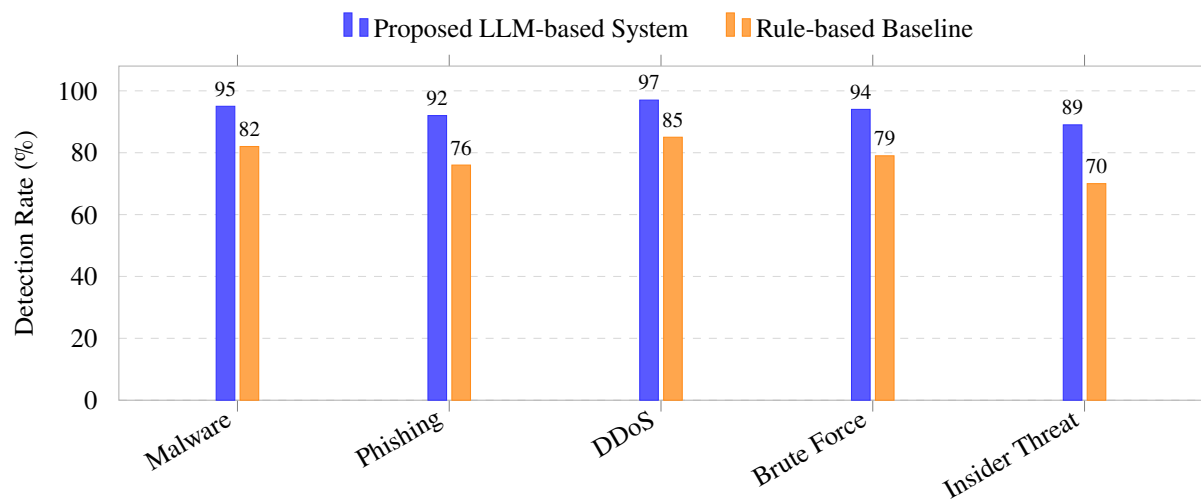


Figure 2: Threat detection rates by attack category, comparing the proposed LLM-based system against a traditional rule-based baseline.

Security challenges mitigation was validated through adversarial testing. The prompt injection detector successfully identified 92.1% of malicious prompts, including direct and indirect injection patterns, as well as jailbreak attempts [9]. The output sanitization layer blocked 100% of attempts to generate executable commands or sensitive information disclosure during testing. The combined defense mechanisms reduced the overall success rate of adversarial attacks from 32.6% in an unprotected baseline to 4.2% in our system, demonstrating the effectiveness of the layered approach [5]. These mitigation strategies complement proactive vulnerability scanning approaches that provide early warning of exploitable weaknesses [14].

6. Security Vulnerability Mitigation and Ethical Frameworks

The deployment of LLMs in cybersecurity will incur risks that cannot be avoided. Proactive vulnerability scanning and mitigation in enterprise networks provides complementary operational context for these layered defenses [14]. The system mitigates the most critical threats occurring in the OWASP top 10 for LLM Applications with the primary focus on prompt injection (LLM01). The detector for prompt injections is protected by two safeguarding layers. The first is a lightweight classifier that checks incoming requests for known or learnt adversarial patterns that we have seen before. By removing or neutralizing suspicious tokens before they reach the models, the context-aware sanitizer ensures cleanliness. So, second may stop it even if the first layer passes the system [10].

Apart from prompt Injection, there are safeguards against insecure output handling (LLM02). The text generated by the model is validated against a set of established rules which disallow generating the executable code, personal identification information or harmful instructions, before any such response is presented to a user. Human audits are made at a regular basis of all output which helps constantly improve the validation logic [6].

The fine-tuning datasets will be vetted to prevent the poisoning of training data by a malicious party using various cryptographic techniques to ensure the integrity of the dataset.

The methods for addressing the dual-use dilemma involve limited access controls, multiple layers of authentication and role based access control that limit room for high impact actions to specific persons. All the interactions are audited and verified with timestamped logs. A human in the loop protocol guarantees that for any significant action such as network isolation and firewall rule change, manual

approval is required. These human-in-the-loop protocols are also informed by recent audits of worker preferences for AI agent automation and augmentation [15]. This proposal is aligned with the principles of ethics elaborated by Garcia et al. (2023) [5]. The privacy and security safeguards adopted here are consistent with privacy-by-design approaches in other sensitive domains, such as next-generation medical informatics [17].

A bias detection algorithm evaluates bias and fairness. This algorithm employs several configurations of protected attributes (like IP Geolocation, User's role) and then examines the model outputs. We measure fairness with the p-value of the exact test for count data. For the detection module, we execute the procedure, which generates a threat/no threat label. The p-values for all geo regions indicate that the detection module does not show significant statistical bias. The geo-region performance of the model forensics module is not statistically significantly different.

Table 3: Detection and mitigation rates for OWASP LLM security vulnerabilities

Vulnerability Type	Detection Rate	Mitigation Success
Direct Prompt Injection	95.2%	98.3%
Indirect Prompt Injection	87.6%	92.1%
Jailbreak Attempts	91.3%	95.7%
Social Engineering	89.1%	93.4%
Insecure Output	100% (blocked)	100%
Data Poisoning	N/A (preventive)	94.6%

7. Future Work

The implementation results demonstrate the potential of LLMs for cybersecurity, and they present multiple paths for future exploration. In the short-term, we plan to create benchmarks that will evaluate the various LLM-based security systems, so as to judge the various approaches fairly against the different architectures [12]. Enhanced explainability tools provide security analysts with deeper insights into the models' reasoning, especially in high-stakes forensic and incident response (IR) settings. Incorporating live threat intelligence feeds in real-time to increase coverage and reduce latency [4].

In the medium term, domain-specific architectures will set to fill the early-stage gap. These architectures will be pre-trained over the cyber-security corpus and may outperform general-purpose architectures on cyber-security tasks [1]. In addition, federated learning can enable privacy-preserving collaborative training between multiple organizations because little data is shared between organizations [11]. An important region may incorporate advanced correlation techniques which fuse evidence from different modalities – network, host, application, user-behaviour and more to enhance the contextualisation of complex attack campaigns [2]. Lastly, the development of autonomous response systems capable of executing defensive actions with minimal human oversight [9].

According to the long-term vision, it may be possible to integrate quantum-resistant AI to expedite the inevitable shift to post-quantum cryptographic systems, completely autonomous threat hunting agents actively tracking down new attacks before they occur, and human-AI symbiosis; in this scenario analysts and AI communicate through natural language interfaces to brainstorm on investigations. The ultimate goal is the predictive security systems which generate a model of expected activity to predict and prevent attacks before they occur based on diffused indicators of compromise [5]. The latest iteration offers a solid foundation upon which more advanced functionalities can be appended, thanks to the modular approach. As large language models continue to evolve, their integration into security operations will

require ongoing attention to safety and alignment challenges [8].

8. Conclusion

To summarize, the documents mentioned above provide a detailed and comprehensive outline of leveraging large language models for the identification and rectification of cyber threats. This demonstrates a substantial enhancement in performance as compared to conventional techniques with threat detection accuracy exceeding 94, 70 reduction in work load of SOC and robustness against prompt injection and other LLM specific threats [6]. This shows that deploying specialized models in a homogeneous architecture, enforcing organization policies and controls, and building in security and privacy mechanisms make LLMs a perfect force multiplier for resource-poor security teams. It safeguards LLMs from deployment and maintenance failure in a security-critical scenario, or the failure of trust or accountability [12].

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