Journal of Data & Digital Innovation

Pages:8-14

Volume-1, Issue-4 (2024)

Hardware Security Enhancements for Energy-Constrained Machine Learning Accelerators

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Abstract

The rapid deployment of machine learning (ML) accelerators in energy-constrained environments such as edge devices, wearable technologies, and Internet of Things (IoT) platforms has intensified the demand for hardware-level security mechanisms. While energy efficiency is a primary design goal for such accelerators, it inadvertently exposes vulnerabilities that adversaries can exploit through side-channel attacks, fault injection, and hardware Trojan insertions. This paper presents an in-depth analysis of hardware security enhancements tailored for energy-constrained ML accelerators. We examine the trade-offs between security and energy consumption, emphasizing the integration of lightweight cryptographic primitives, secure memory hierarchies, and tamper-resistant architectures. Experimental evaluations were conducted on FPGA-based prototypes implementing deep neural network accelerators with integrated security modules. Results demonstrate that lightweight security primitives can achieve up to 30% energy reduction compared to conventional cryptographic methods while maintaining robust resistance against attacks. The findings suggest that balancing efficiency and trustworthiness in ML accelerators is critical to enabling secure, low-power intelligent systems at scale.

Keywords: Hardware Security, Machine Learning Accelerators, Energy-Constrained Systems, Side-Channel Attacks, Secure Architectures, IoT Security

I. Introduction

The proliferation of artificial intelligence (AI) in edge and embedded environments has been fueled by specialized hardware accelerators designed for machine learning workloads. These accelerators, often deployed in battery-operated or energy-constrained platforms, prioritize energy efficiency and low latency to meet real-time processing demands. However, the emphasis on energy minimization often comes at the expense of integrated security mechanisms, making such accelerators prime targets for adversarial exploitation. Attacks that exploit physical vulnerabilities, such as power analysis or electromagnetic emissions, can leak sensitive model parameters and compromise intellectual property. In contexts such as healthcare, autonomous systems, and financial applications, these threats have severe implications for privacy, safety, and trust [1]. The security of machine learning hardware accelerators is fundamentally different from traditional computing platforms. Unlike general-purpose processors, ML accelerators rely on optimized memory hierarchies, specialized compute units, and custom dataflows that limit the applicability of software-based protection. Furthermore, energy-constrained environments require lightweight and resource-aware mechanisms that do not undermine the power savings gained through architectural innovations. This has led researchers to explore hardware-level countermeasures that are tailored to the unique operating characteristics of ML accelerators [2].

A critical challenge in designing secure ML accelerators is the trade-off between energy efficiency and resilience against physical attacks. For instance, adding redundancy, shielding, or cryptographic protections increases power overhead, potentially violating system energy budgets. To address this, novel strategies such as approximate cryptographic primitives, hardware randomization, and selective obfuscation have been proposed to achieve security without excessive resource consumption. These methods must be rigorously evaluated not only for their theoretical resistance to adversaries but also for their practical feasibility in real-world deployments. The contribution of this research lies in providing a comprehensive framework for hardware security enhancements in energy-constrained ML accelerators. By analyzing vulnerabilities, proposing lightweight hardware primitives, and experimentally validating their performance, this study bridges the gap between security research and hardware design optimization. In doing so, it paves the way for secure and sustainable ML deployment in next-generation computing environments [3].

II. Literature Review

The existing body of research on hardware security has predominantly focused on high-performance computing systems, where energy constraints are less stringent. Conventional approaches employ strong cryptographic primitives, trusted execution environments, and secure co-processors. While effective in server-class systems, these methods impose prohibitive energy and area costs when translated to embedded ML accelerators. For example, implementations of AES or RSA incur significant power and latency overheads, making them unsuitable for edge devices with limited resources [4]. This has prompted a search for lightweight alternatives. Studies on side-channel attack mitigation have explored techniques such as masking, hiding, and noise injection. Masking involves randomizing intermediate computations, while hiding attempts to equalize power consumption across operations. However, these methods often degrade performance and inflate power budgets, rendering them less attractive for low-energy accelerators. Recent efforts have instead focused on integrating approximate security primitives, such as low-cost block ciphers like PRESENT or SIMON, which provide moderate levels of security with drastically reduced energy footprints.

Hardware Trojan detection and prevention also play an important role in ensuring the integrity of ML accelerators. Trojans can be inserted during manufacturing or design phases, allowing adversaries to exfiltrate data or sabotage computations. Lightweight detection frameworks leverage runtime monitoring of power signatures and timing behavior to flag anomalies. Additionally, physically unclonable functions (PUFs) have been widely adopted as a cost-effective method to establish device identity and authentication without requiring energy-expensive key storage. The literature also highlights the growing importance of secure memory hierarchies for ML accelerators. Since models and training data are often stored in off-chip

DRAM or flash memory, attackers can exploit vulnerabilities during data transfer. Techniques such as in-memory encryption, lightweight integrity verification, and secure scratchpad designs have been proposed to address these threats. Collectively, these studies emphasize that the challenge is not only to provide protection but to integrate it seamlessly within the energy and performance constraints of the accelerator.

Despite these advancements, there remains a lack of holistic frameworks that balance energy efficiency, hardware complexity, and security robustness. Many studies evaluate isolated countermeasures without addressing their system-level impact. This paper addresses this gap by experimentally analyzing lightweight hardware security enhancements within ML accelerators, providing insights into trade-offs and performance impacts.

III. Methodology

To evaluate the feasibility of integrating hardware security enhancements in energy-constrained ML accelerators, a multi-stage methodology was employed. First, common attack vectors for ML accelerators were identified, including side-channel analysis, fault injection, and hardware Trojan activation. These threats were modeled within an FPGA-based experimental platform, enabling controlled and repeatable evaluations of countermeasures. The chosen ML accelerator implemented a convolutional neural network (CNN) optimized for image classification tasks, reflecting a representative workload in edge AI applications. Next, lightweight hardware primitives were integrated into the accelerator design. These included a PRESENT-based cryptographic engine for data protection, PUF-based device authentication for securing access, and lightweight error-detection codes to mitigate fault injection attacks. Each primitive was carefully parameterized to minimize area and power overheads while maintaining adequate resistance levels [5]. For instance, the cryptographic engine was implemented using serial architectures to reduce switching activity, and PUF circuits were optimized to exploit intrinsic process variations without requiring additional energy-consuming components.

The accelerator was synthesized and deployed on a Xilinx Zynq FPGA platform, chosen for its support of both programmable logic and embedded processing. Power consumption was measured using on-board sensors, while performance was evaluated through classification accuracy, latency, and throughput benchmarks. Security evaluation was performed by executing simulated attack scenarios, including differential power analysis and clock glitching, to determine the robustness of the integrated primitives [6]. Comparative analysis was conducted against a baseline accelerator without security enhancements and a variant employing conventional AES encryption. The baseline provided insights into raw energy efficiency, while the AES variant illustrated the trade-offs of employing heavyweight cryptographic methods. By systematically evaluating these implementations, we sought to quantify the energy-security balance achievable through lightweight enhancements. The methodology emphasizes system-level validation rather than isolated component testing. This approach ensures that the insights derived are relevant for practical deployments where ML accelerators operate in dynamic, resource-limited environments [7].

IV. Experimental Results and Discussion

The experimental results highlight the effectiveness of integrating lightweight security primitives into energy-constrained ML accelerators [8]. The baseline accelerator consumed the least energy but was entirely vulnerable to side-channel and fault injection attacks. In contrast, the AES-secured accelerator offered strong protection but introduced a 45% increase in power consumption and a 28% latency penalty, rendering it impractical for battery-powered environments [9]. The proposed lightweight security-enhanced accelerator achieved a favorable balance. Energy consumption increased by only 12% compared to the baseline, significantly lower than the AES-secured implementation. Performance degradation was minimal, with less than a 5% increase in latency and negligible impact on throughput. Most importantly, the integrated security primitives demonstrated substantial resilience: differential power analysis attacks required orders of magnitude more traces to succeed, while clock glitching was effectively mitigated through error-detection codes [10].

Classification accuracy remained unaffected, underscoring that the security enhancements did not interfere with the correctness of ML operations. Furthermore, PUF-based authentication successfully generated unique identifiers across multiple FPGA instances with high reliability, providing a secure basis for device-level trust establishment. These results confirm that lightweight primitives can deliver effective protection without undermining the primary goal of energy efficiency [10].

A deeper analysis revealed that the trade-off between security strength and energy efficiency can be tuned by adjusting primitive configurations. For instance, using fewer encryption rounds reduced energy overhead but lowered attack resistance, suggesting a customizable framework based on application requirements. In scenarios such as medical monitoring, where data confidentiality is paramount, stronger configurations may be justified, while less critical tasks can adopt more energy-lean settings. Overall, the findings emphasize the feasibility of designing secure and energy-efficient ML accelerators for real-world edge applications [11]. By adopting tailored hardware primitives rather than generic solutions, it is possible to mitigate vulnerabilities without sacrificing the sustainability and responsiveness that characterize edge intelligence.

V. Conclusion

This research demonstrates that hardware security enhancements tailored for energy-constrained machine learning accelerators can successfully balance the competing demands of efficiency and robustness. Through FPGA-based experiments, lightweight primitives such as PRESENT encryption, PUF authentication, and error-detection codes proved capable of significantly improving resistance to side-channel and fault injection attacks with only modest energy and performance overheads. Unlike conventional cryptographic approaches, which impose prohibitive costs in resource-limited environments, these lightweight methods enable practical and scalable deployment of secure ML accelerators at the edge. The study highlights that achieving trustworthy AI systems in energy-constrained environments requires co-optimizing security and efficiency at the hardware design level, paving the way for the next generation of secure, intelligent, and sustainable computing platforms.

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