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Abstract: Companies, in their push to incorporate artificial intelligence - in particular, machine learning - into their Internet of Things (IoT), system-on-chip (SoC), and automotive applications, will have to address a number of design challenges related to the secure deployment of artificial intelligence learning models and techniques. Machine learning (ML) models are often trained using private datasets that are very expensive to collect, or highly sensitive, using large amounts of computing power. The models are commonly exposed either through online APIs, or used in hardware devices deployed in the field or given to the end users. This gives incentives to adversaries to attempt to steal these ML models as a proxy for gathering datasets. While API-based model exfiltration has been studied before, the theft and protection of machine learning models on hardware devices have not been explored as of now. In this work, we examine this important aspect of the design and deployment of ML models. We illustrate how an attacker may acquire either the model or the model architecture through memory probing, side-channels, or crafted input attacks, and propose (1) power-efficient obfuscation as an alternative to encryption, and (2) timing side-channel countermeasures.