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Sommario/riassunto

An expert compilation of on-device training techniques, regulatory frameworks, and ethical considerations of TinyML design and development In Tiny Machine Learning: Design Principles and Applications, a team of distinguished researchers delivers a comprehensive discussion of the critical concepts, design principles, applications, and relevant.
