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## Sommario/riassunto

This book discusses recent advances in the application of deep learning techniques to electromagnetic theory and engineering. The contents represent pioneer applications of deep learning techniques to

electromagnetic engineering, where physical principles described by the Maxwell's equations dominate.

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