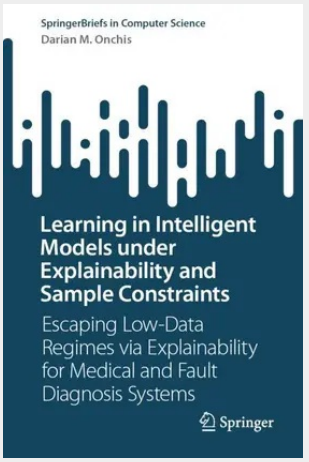
Onchis

Learning in Intelligent Models under Explainability and Sample Constraints

Escaping Low-Data Regimes via Explainability for Medical and Fault Diagnosis Systems



This book provides a unified framework for learning in intelligent systems under conditions of limited data and strict explainability requirements. It addresses a critical gap in modern machine learning, where high-performance models often rely on large datasets and operate as black boxes, limiting their applicability in high-stakes domains.The book introduces the LIMESC framework, a novel approach that integrates explainability, learning, and domain knowledge into a single methodological structure. It systematically explores how models can remain robust, interpretable, and adaptable when data are scarce, noisy, or evolving.Core topics include neural computing, deep learning under small-data regimes, regularization and optimization strategies, class-incremental learning without memory, and dataset knowledge transfer. The book further examines post-hoc explainability methods and transitions toward intrinsic interpretability through causal and neuro-symbolic approaches. Additional perspectives such as topological data analysis and reinforcement learning in constrained environments are also presented.The framework is grounded in real-world applications, particularly medical diagnostics and fault detection systems, where explainability and reliability are essential. Through a combination of theoretical insights and practical methodologies, the book offers a structured pathway toward designing adaptive and interpretable machine learning systems.This book is intended for researchers, advanced graduate students, and practitioners in machine learning, artificial intelligence, and biomedical engineering.

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