Industrial Artificial Intelligence Technologies and Applications

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Industrial Artificial Intelligence Technologies and Applications

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"Without change there is no innovation, creativity, or incentive for improvement. Those who initiate change will have a better opportunity to manage the change that is inevitable."

- William Pollard

"The brain is like a muscle. When it is in use we feel very good. Understanding is joyous."

- Carl Sagan

"By far, the greatest danger of Artificial Intelligence is that people conclude too early that they understand it."

- Eliezer Yudkowsky

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Ovidiu Vermesan
Franz Wotawa
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Preface

Industrial Artificial Intelligence Technologies and Applications

Digitalisation and Industry 5.0 are changing how manufacturing facilities operate by deploying many sensors/actuators, edge computing, and IIoT devices and forming intelligent networks of collaborative machines that are able to collect, aggregate, and intelligently process data at a network's edge.

Given the vast amount of data produced by IIoT devices, computing at the edge is required. In this context, edge computing plays an important role – the edge should provide computing resources for edge intelligence with dependability, data management, and aggregation provision in mind. Edge intelligence – for example, AI technologies with edge computing for training/learning, testing, or inference – is essential for IIoT applications to build models that can learn from a large amount of aggregated data.

Edge computing is a distributed computing paradigm that brings computation and data storage closer to a device's location. AI algorithms process the data created on a device with or without an internet connection. These new AI-based algorithms allow data to be processed within a few milliseconds, providing real-time feedback.

The AI models operate on the devices themselves without the need for a cloud connection and without the problems associated with data latency, which results in much faster data processing and support for use cases that require real-time inferencing.

Major challenges remain in achieving this potential due to the inherent complexity of designing and deploying energy-efficient edge AI algorithms and architectures, the intricacy of complex variations in neural network architectures, and the underlying limited processing capabilities of edge AI accelerators.

Industrial-edge AI can run on various hardware platforms, from ordinary microcontrollers (MCUs) to advanced neural processing devices. IIoT edge AI-connected devices use embedded algorithms to monitor device behaviour and collect and process device data. Devices make decisions, automatically correct problems, and predict future performance.

AI-based technologies are used across industries by introducing intelligent techniques, including machine and deep learning, cognitive computing, and computer vision. The application of the techniques and methods of AI in the industrial sector is a crucial reference source that provides vital research on implementing advanced technological techniques in this sector.

This book offers comprehensive coverage of the topics presented at the "International Workshop on Edge Artificial Intelligence for Industrial Applications (EAI4IA)" in Vienna, 25-26 July 2022. EAI4IA is co-located with the 31st International Joint Conference on Artificial Intelligence and the 23rd European Conference on Artificial Intelligence (IJCAI-ECAI 2022). It combines the ideas and concepts developed by researchers and practitioners working on providing edge AI methods, techniques, and tools for use in industrial applications.

By highlighting important topics, such as embedded AI for semiconductor manufacturing and trustworthy, dependable, and explainable AI for the digitising industry, verification, validation and benchmarking of AI systems and technologies, AI model development workflows and hardware target platforms deployment, the book explores the challenges faced by AI technologies deployed in various industrial application domains.

The book is ideally structured and designed for researchers, developers, managers, academics, analysts, post-graduate students, and practitioners seeking current research on the involvement of industrial-edge AI. It combines the latest methodologies, tools, and techniques related to AI and IIoT in a joint volume to build insight into their sustainable deployment in various industrial sectors.

The book is structured around four different topics:

1. **Verification, Validation and Benchmarking of AI Systems and Technologies.**
2. **Trustworthy, Dependable AI for Digitising Industry.**
3. **Embedded AI for semiconductor manufacturing.**
4. **AI model development workflow and HW target platforms deployment.**

In the following, the papers published in this book are briefly discussed.

S. Narduzzi, L. Mateu, P. Jokic, E. Azarkhish, and A. Dunbar: "Benchmarking Neuromorphic Computing for Inference" tackle the challenge of benchmarking aiming at providing a fair and user-friendly method. The authors introduce the challenge and finally come up with possible key performance indicators.

M. Molendijk, K. Vadivel, F. Corradi, G-J. van Schaik, A. Yousefzadeh, and H. Corporaal: "Benchmarking the Epiphany Processor as a Reference Neuromorphic Architecture" compare different implementations of neuromorphic processors and present suggestions for improvements.

P. Vijayan, A. Yousefzadeh, M. Sifalakis, and R. van Leuken: "Temporal Delta Layer: Exploiting Temporal Sparsity in Deep Neural Networks for Time-Series Data" deal with improving the learning of time-series data in the context of deep neural networks. In particular, the authors consider sparsity and show experimentally overall improvements.

D. Purice, M. Ludwig, and C. Lenz: "An End-to-End AI-based Automated Process for Semiconductor Device Parameter Extraction" present a validation pipeline aiming at gaining trust in semiconductor devices relying on authenticity checking. The authors further evaluate their approach by considering several artificial neural network architectures.

D. Morits, M. Rizzo Piton, and T. Laakko: "AI machine vision system for wafer defect detection" discuss the use of machine learning for fault detection based on images in the context of semiconductor manufacturing.

S. Al-Baddai and J. Papadoudis: "Failure detection in silicon package" discuss the use of machine learning techniques for wire-bonding inspection occurring during the packaging of semiconductors. The authors report on the accuracy of failure detection using machine learning in the complex industrial environment.

X. L. Liu, Eileen Salhofer, A. Safont Andreu, and R. Kern: "S2ORC-SemiCause: Annotating and analysing causality in the semiconductor domain" introduce a benchmark dataset to be used in the context of cause-effect reasoning for extracting causal relations.

A. Wandesleben, D. Truffier-Boutry, V. Brackmann, B. Lilienthal-Uhlig, M. Jaysnkar, S. Beckx, I. Madarevic, A. Demarest, B. Hintze, F. Hochschulz, Y. Le Tiec, A. Spessot, and F. Nemouchi: "Feasibility of wafer exchange for European Edge AI pilot lines" focus on contamination monitoring for allowing to exchange wafers among different facilities. In particular, the authors presented an analysis of whether such an exchange would be feasible considering three European research institutes.

D. Kaufmann and F. Wotawa: "A framework for integrating automated diagnosis into simulation" discuss a framework that allows the integration of model-based diagnosis algorithms in physical simulation. The framework can be used for verifying and validating diagnosis implementations for cyber-physical systems.

S. Narduzzi, D. Favre, N. Pazos Escudero, and A. Dunbar: “Deploying a Convolutional Neural Network on Edge MCU and Neuromorphic Hardware Platforms” discuss the deployment of neural networks for edge computing considering different platforms. The authors also report on the perceived effort of deployment for each of the platforms.

R. Prokscha, M. Schneider, and A. Höß: “Efficient Edge Deployment Demonstrated on YOLOv5 and Coral Edge TPU”consider the question of deployment of machine learning on the edge.

O. Vermesan and M. Coppola: ”Embedded Edge Intelligent Processing for End-To-End Predictive Maintenance in Industrial Applications” presented the use of machine learning for edge computing supporting predictive maintenance using different technologies, workflows, and datasets.

L. A. Steffenel, A. Langlet, L. Hollard, L. Mohimont, N. Gaveau, M. Copola, C. Pierlot, and M. Rondeau: ”AI-Driven Strategies to Implement a Grapevine Downy Mildew Warning System” outline the use of machine learning for identifying infections occurring in vineyards and present an experimental evaluation comparing different machine learning algorithms.

F. Wotawa and O. Tazl: ”On the Verification of Diagnosis Models” focus on challenges of verification and in particular testing applied to logic-based diagnosis. The authors consider testing system models and use a running example for demonstrating how such models can be tested and come up with open research questions.

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