
**Artificial Intelligence for
Digitising Industry
Applications**

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Artificial Intelligence for Digitising Industry Applications

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Dedication

“Action is the real measure of intelligence.”

- Napoleon Hill

“Intelligence is the ability to adapt to change.”

- Stephen Hawking

“Intelligence is quickness in seeing things as they are.”

- George Santayana

“Everything you can imagine is real.”

- Pablo Picasso

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Preface

Artificial Intelligence for Digitising Industry – Applications

Industry 4.0 has revolutionised the manufacturing sector by integrating several technologies, including cloud computing, big data, and cyber-physical systems. The goal of Industry 4.0 is to make the manufacturing industry “smart” by integrating machines and equipment that can be monitored and controlled throughout the life cycle.

Industry 5.0 extends technological advances to further facilitate intelligent machine-machine and human-machine collaboration. The goal is to combine the speed, precision, repeatability, and replicability of the operation of machines with the vision, decision-making, and critical and cognitive thinking of human beings. Industry 5.0 can significantly increase the efficiency of manufacturing by extending the use of AI technologies to create a versatile connection between humans and machines, enabling constant monitoring and interaction. This collaboration will enhance the speed and the quality of production by assigning repetitive tasks to intelligent robots and other machines and fostering critical thinking by human beings. Industry 5.0 is characterized by the convergence of technologies and integrates the industrial internet of things (IIoT) with AI-based solutions and digital twins to connect physical and virtual manufacturing environments. This convergence makes possible physical and virtual simulations and operating environments in which models based on predictive analytics and managed intelligence enable faster, more accurate and precise, and more reliable decisions. This approach may also provide greener solutions than those of current industrial facilities: end-to-end, environmentally friendly manufacturing solutions with a minimal CO₂ footprint.

AI is transforming industrial environments. Edge-based AI technologies mitigate operational risk, improve the safety and efficiency of manufacturing, optimise processes, and form more reliable and sustainable manufacturing facilities. Adopting AI technology across industrial sectors enables more accurate prediction of anomalies and malfunctions, better management of

resource consumption, and optimising of manufacturing processes. Artificial intelligence is expected to significantly impact global manufacturing and industrial development. Integrated with other technologies - like intelligent sensors, IIoT, digital twins, edge computing, augmented reality, intelligent wireless and cellular connectivity - AI optimises production in real time and facilitates vertical, horizontal, and end-to-end integration.

AI industrial applications harness artificial intelligence to enhance efficiency and sustainability while expediting digital transformations. By applying AI, machine learning, and deep learning, manufacturers can advance operational efficiency, dynamically control, and adapt product lines, customise product designs, and plan technological developments.

This book explores the research, practical results, and exchange of ideas between the representatives of forty-one organisations participating in the AI4DI project to develop the technological community. The concepts presented herein reflect interaction with other European and international projects addressing the research, development, and deployment of AI, IIoT, edge computing, digital twins, and robotics in industrial environments to strengthen and sustain a dynamic AI technology ecosystem. These concepts and research results shed light on steps in the evolutionary transition to Industry 5.0. The focus is on five industries: the automotive, semiconductor, industrial machinery, food and beverage, and transportation industries.

The AI4DI project is part of the Electronic Components and Systems for European Leadership Joint Undertaking (ECSEL JU) programme, and the applications and technologies developed by the project partners support the digital transformation of the industry. They are aligned with the priorities of the new European partnership for Key Digital Technologies (KDT). KDT aims to provide innovative electronic components and systems, software, and smart integration to digital value chains, providing secure and trusted technologies tailored to the needs of user industries and citizens to support and reinforce Europe's potential to innovate. The goal is to develop and apply these technologies to address significant global challenges in mobility, health, energy, security, manufacturing, and digital communications.

The alignment between research, innovation, and industrial policies by using collaborative approaches in mastering the drivers of innovation contributes to and strengthens Europe's scientific and technological bases.

Editors Biography

Dr. Ovidiu Vermesan holds a PhD degree in microelectronics and a Master of International Business (MIB) degree. He is Chief Scientist at SINTEF Digital, Oslo, Norway. His research interests are in the area of smart systems integration, mixed-signal embedded electronics, analogue neural networks, artificial intelligence (AI) and cognitive communication systems. Dr. Vermesan received SINTEF's 2003 award for research excellence for his work on the implementation of a biometric sensor system. He is currently working on projects addressing nanoelectronics, integrated sensor/actuator systems, communication, cyber-physical systems (CPSs) and Industrial Internet of Things (IIoT), industrial AI with applications in green mobility, energy, autonomous systems, and smart cities. He has authored or co-authored over 85 technical articles and conference papers. He is actively involved in the activities of the Electronic Components and Systems for European Leadership Joint Undertaking (ECSEL JU) and involved in technical activities to define the priorities for the new European partnership for Key Digital Technologies (KDT). He has coordinated and managed various national, EU and other international projects related to smart sensor systems, integrated electronics, electromobility and intelligent autonomous systems such as E³Car, POLLUX, CASTOR, IoE, MIRANDELA, IoF2020, AUTOPILOT, AutoDrive, ArchitectECA2030, AI4DI, AI4CSM. Dr. Vermesan actively participates in national, H2020 EU and other international initiatives by coordinating and managing various projects. He is the coordinator of the IoT European Research Cluster (IERC) and a member of the board of the Alliance for Internet of Things Innovation (AIOTI). He is currently the technical co-coordinator of the ECSEL Artificial Intelligence for Digitising Industry (AI4DI) project.

Reiner John received his degree in Electrical Engineering from the Fachhochschule des Saarlandes (Germany) in collaboration with the University of Metz / Perpignan (France). In 1984 he started his career with the Siemens Semiconductor Group in Munich, where he worked in

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Marcello Coppola is technical Director at STMicroelectronics. He has more than 25 years of industry experience with an extended network within the research community and major funding agencies with the primary focus on the development of break-through technologies. He is a technology innovator, with the ability to accurately predict technology trends. He is involved in many European research projects targeting Industrial IoT and IoT, cyber physical systems, Smart Agriculture, AI, Low power, Security, 5G, and design technologies for Multicore and Many-core System-on-Chip, with particular emphasis to architecture and network-on-chip. He has published more than 50 scientific publications, holds over 26 issued patents. He authored chapters in 12 edited print books, and he is one of the main authors of “Design of Cost-Efficient Interconnect Processing Units: Spidergon STNoC” book. Until 2018, he was part of IEEE Computing Now Journal Technical editorial board. He contributed to the security chapter of the Strategic Research Agenda (SRA) to set the scene on R&I on Embedded Intelligent Systems in Europe. He is serving under different roles numerous top international conferences and workshops. Graduated in Computer Science from the University of Pisa, Italy in 1992.

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List of Abbreviations

AI	Artificial intelligence
AI4DI	Artificial intelligence for digitizing industry
ANN	Artificial neural networks
API	Application programming interface
APMF	Approximate progressive morphological filter
ASIC	Application-specific integrated circuit
BLE	Bluetooth low energy
BMS	Battery management system
BRAM	Block RAM
CatE	Computing-at-the-Edge
CBM	Condition-based maintenance
CM	Confusion matrices
CNN	Convolutional neural networks
CPU	Central processing unit
CUDA	Compute unified device architecture
DC	Direct current
DFB	Data fusion bus
DL	Deep learning
DMA	Direct memory access
DNN	Deep neural network
ECSEL JU	Electronic components and systems for european leadership - joint undertaking
EDR	Errors-to-Data Ratio
EIS	Electrochemical impedance spectroscopy
EMF	Electro motive force
EOL	End of life
ERP	Enterprise resource planning
ETL	Extract, transform, load
EV	Electric vehicle
FF	Flip-flop

FFT	Fast fourier transform
FoV	Field of view
FPGA	Field programmable gate arrays
GPS	Global positioning system
GPU	Graphics processing unit
HDMI	High-definition multimedia interface
HIL	Hardware-in-the-Loop
HLS	High level synthesis
HMI	Human machine interface, human machine interaction
HTTPS	Hypertext transfer protocol secure
HW	Hardware
IDE	Integrated development environment
IIoIT	Industrial internet of intelligent things
IIoT	Industrial internet of things
IMU	Inertial measurement unit
ITS	Intelligent transport systems
JSON	JavaScript object notation
LIB	Lithium-ion battery
Lidar	Light detection and ranging
LoRa	Long range (modulation technique)
LoRaWAN	LoRa wide area network
LTE	Long-term evolution (standard for wireless broadband)
LSQ	Learned step size quantization
LUT	Lookup table
MaaS	Mobility as a service
MBD	Model-based diagnosis
MIR	Multimedia information retrieval
ML	Machine learning
MLP	Multilayer perceptron
MPDSS	Material planning decision support system
MQTT	Message queuing telemetry transport
MSE	Mean squared error
N2D2	Neural network design & deployment
NFR	Non-functional requirements
NN	Neural networks
OEM	Original equipment manufacturer
ONNX	Open neural network exchange
OPC	Open platform communication

OPC UA	OPC unified architecture
OpenDDS	Open data distribution service
OS	Operating system
OSM	Open street map
PdM	Predictive maintenance
PLC	Programmable logic controllers
PMSM	Permanent magnet synchronous motor
PTQ	Post training quantization
PvM	Preventive maintenance
QAT	Quantization aware training
R2F	Run to failure
RAM	Random access memory
RDBMS	Relational database management system
RESTful	Representational state transfer, world wide web services that satisfy the REST constraints is described as RESTful.
RGB	Red-Green-Blue
RL	Reinforcement learning
SAT	Scale-adjusted training
SCADA	Supervisory control and data acquisition
SCM	Supply chain management
SIRI	Service interface for real time information
SoC	System-on-Chip
SOH	State of health
SW	Software
TCN	Temporal convolutional network
TensorRT	TensorRT is an SDK for high-performance deep learning inference from NVIDIA
TPU	Tensor processing unit
UI	User interface
YOLO	You only look once

