From Artificial Intelligence to Explainable Artificial Intelligence in Industry 4.0: A Survey on What, How, and Where

Imran Ahmed, *Senior Member, IEEE*, Gwanggil Jeon, *Senior Member, IEEE*, and Francesco Piccialli, *Member, IEEE*

***Abstract*—Nowadays, Industry 4.0 can be considered a reality, a paradigm integrating modern technologies and innovations. Artificial intelligence (AI) can be considered the leading component of the industrial transformation enabling intelligent machines to execute tasks autonomously such as self-monitoring, interpretation, diagnosis, and analysis. AI-based methodologies (especially machine learning and deep learning support manufacturers and industries in predicting their maintenance needs and reducing downtime. Explainable artificial intelligence (XAI) studies and designs approaches, algorithms and tools producing human-understandable explanations of AI-based systems information and decisions. This article presents a comprehensive survey of AI and XAI-based methods adopted in the Industry 4.0 scenario. First, we briefly discuss different technologies enabling Industry 4.0. Then, we present an in-depth investigation of the main methods used in the literature: we also provide the details of what, how, why, and where these methods have been applied for Industry 4.0. Furthermore, we illustrate the opportunities and challenges that elicit future research directions toward responsible or human-centric AI and XAI systems, essential for adopting high-stakes industry applications.**

***Index Terms*—Artificial intelligence (AI), cloud computing, cyber-physical system, explainable artificial intelligence (XAI), Industry 4.0, Internet of Things (IoT).**

Manuscript received May 7, 2021; revised August 6, 2021, November 3, 2021, and January 9, 2022; accepted January 20, 2022. Date of publication January 27, 2022; date of current version May 6, 2022. This work was supported by the project titled "4I: mixed reality, machine learning, gamification and educational for Industry," Prog. n. F/190130/01-03/X44, Fondo per la Crescita Sostenibile—Sportello "Fabbrica Intelligente" PON I & C 2014-2020, CUP: B66G21000040005 COR: 4641138. Paper no. TII-21-1915. *(Corresponding authors: Francesco Piccialli; Gwanggil Jeon.)*

Imran Ahmed is with the Center of Excellence in Information Technology, Institute of Management Sciences, Hayatabad, Peshawar 25000, Pakistan (e-mail: imran.ahmed@imsciences.edu.pk).

Gwanggil Jeon is with the Department of Embedded Systems Engineering, Incheon National University, Incheon 406-772, South Korea (e-mail: gjeon@inu.ac.kr).

Francesco Piccialli is with the Department of Mathematics and Applications "R.Caccioppoli," University of Naples Federico II, 80138 Naples, Italy (e-mail: francesco.piccialli@unina.it).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TII.2022.3146552.

Digital Object Identifier 10.1109/TII.2022.3146552

I. Introduction

THE first industrial transformation began using steam and water power, while the second industrial transformation started mass production through electricity. The third revolution raised the involvement of computers and electronics in the industry; the forthcoming industrial revolution, called Industry 4.0, integrates automation and digital twin technologies as illustrated in Fig. 1. Thus, Industry 4.0 has been interpreted as "the new direction of automation and digital data transfer in manufacturing and similar technologies, including Internet of Things (IoT), cyber-physical systems, cloud computing, systems integration, big-data analytics that services in establishing the smart industries and factories." Industry 4.0 includes the intelligent network of devices, machines, and systems for industries with the help of communication and technology. The advancement of AI and the use of machine learning (ML) and deep learning (DL) based methods in industries are leveraging their applications to be part of Industry 4.0. AI applications have made progress in solving automatic recognition of patterns in data. AI-based systems can assist subject matter experts as they perform evaluations in the background of their work activities, particularly when complex knowledge and strategies are concerned. The targeted application of data-driven and decision-making may influence meaningful productivity gains in the industry sectors, allowing a successful operationalization and embedding cognitive insights into the business processes. Such integration needs an advanced management process, which develops trust in the actions, inference mechanisms, and results of the extended AI-based systems. However, for a stable deployment of the artificial intelligence (AI) based systems and their acceptance by the experts, decisions, and results must be comprehensible or understandable; in other words, "Explainable."

In this scenario, this work aims to provide a comprehensive survey of AI, explainable artificial intelligence (XAI) based methods, and applications in Industry 4.0. We considered more than 1000 published articles extracted from the dimensions database.[1] The dataset has been extracted using the keyword articles related to "Industry 4.0," "IoT," "AI," and "XAI." We first discussed Industry 4.0 related technologies and then briefly summarized different AI and XAI-based methods. Next, we present how, why, and where AI and XAI are adopted in various enabling Industry 4.0. We also categorized the applications

[1][Online]. Available: https://app.dimensions.ai/discover/publication/

TABLE I
SUMMARY OF RECENT ADVANCED TECHNOLOGIES ENABLING INDUSTRY 4.0

Technology	Application	Technology Description	Main Contribution Summary
IoT [1]	Manufacturing	Networking of smart physical objects (sensors, devices, machines, cameras, vehicles, buildings). Allows exchange and collection of data, communication, and collaboration of objects.	Presented a brief summary of Industry 4.0 and associated technologies.
Big data [2]	Business	Selection and evaluation of extensively available data sets. Applying a set of methods to clean, record the data. Present observations during data processing with various variety, higher velocities in greater volumes of data.	Investigate the operational and necessary impacts of Big data. Presented systematic analysis and case study conclusions. Studied the applications and highlight future directions.
Cloud Computing [3]	Industry 4.0.	System for establishing online storage functions (data applications). Models, and programs in a virtual server.	Explored emerging IT trends: IoT, Big data, and Cloud Computing. Investigates their industrial implementation.
Augmented reality [4]	Industry	Collection of HCI methods can insert virtual objects. Collaborate in the physical environment.	Presented overview of the importance of Augmented reality.
Cyber-physical system [5]	Industry 4.0	Set of advanced technologies, link the processes of physical resources and computational capacities, control physical systems, while designing a virtual model.	Reviewed current research trends of cyber-physical systems, their applications in industries and identifies challenges.
System Integration [6]	Manufacturing	Establishment of a standard data network system. Allows various organizations and departments to be integrated and linked, where a smooth collaboration and computerized value chains are feasibly formed.	Review important aspects of additive manufacturing: new improvements in process development and material science. Analyze modern science and technological trends) and highlight its possible applications.
Autonomous robotics [7]	Automation & Robotic	Instrument and machinery that automate operational processes, consisting of collaborative robotics, enables machines and humans to operate and interact in a distributed learning environment.	Review on the progress of robotic and mechanization technology for industrial applications.
Simulation [8]	Manufacturing	Technologies that illustrate real-life data like products, systems, and humans in the real world, intending for interpretation and affordability of the system, design, experimentation, and live development of the processes.	Analyze ongoing research trends of Industry 4.0, highlights important design systems and technology aims, distinguish its architectural layout, and direct strategic road maps.
Additive manufacturing [6]	Manufacturing	Process of combining objects in subsequent layers to create objects using data of 3D model and 'unlock' system choices to accomplish high potential for mass customization.	Focus on the principle concept of Industry 4.0. Identify research gaps between modern systems and Industry 4.0 requirements.

of Industry 4.0. Finally, we discussed challenges and future trends regarding AI and XAI in Industry 4.0. In summary, the contributions of this survey can be listed as follows.

1) An overview of the key technologies of Industry 4.0, the different types of AI methods and XAI approaches used in Industry 4.0.
2) How, why, and where AI and XAI-based methods and advanced technologies are used in Industry 4.0.
3) A presentation of the applications related to AI and XAI in Industry 4.0.
4) An analysis of the recent and open challenges related to AI and XAI in Industry 4.0, with future research directions.

The rest of this article is organized as follows. In Section II, we will present various technologies that enable Industry 4.0. In Sections III and IV, we will discuss various types of AI and XAI-based methods or approaches applied in Industry 4.0. Section V elaborated different applications of the presented techniques in Industry 4.0. Section VI exhibits current challenges about applying AI and XAI based techniques in industrial applications and outlines future research directions. Finally, Section VII concludes this article.

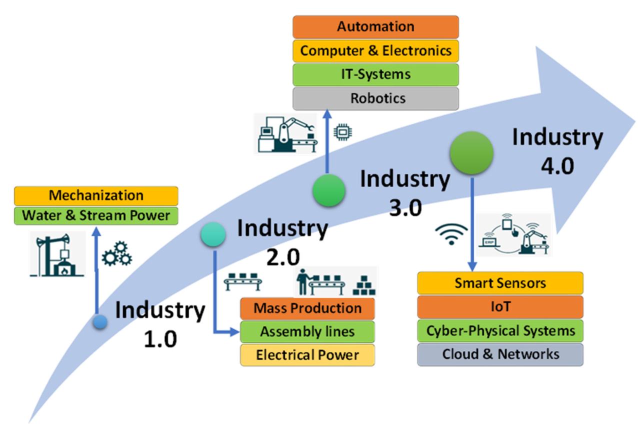


Fig. 1. Schematic illustration of the four industrial revolutions.

II. TECHNOLOGIES OF INDUSTRY 4.0

Industry 4.0 represents a popular concept in the manufacturing and industrial realm. The initial goals typically involve automation, process development, and productivity improvement; the more advanced goals concentrate on modernization, interoperability, and evolution of different intelligent systems or models with information and co-operations as essential. The main idea of Industry 4.0 is to produce extraordinary operational performance and productivity and, at the same time, a powerful level of automatization. In addition, Industry 4.0 intends to provide intelligent, real time, smart, interoperable, and independent industrial environments [9]. To achieve this goal, improved, innovative information, data mining, technologies, including IoT [1], big data [2], cloud computing [3], augmented reality [4], cyber-physical system [5], system integration [6], robotics [7], simulation [8], and additive manufacturing [6] are integrated, as presented in Fig. 2. Table I provides a summary of associated technologies used in various industrial applications, which is structured as follows: the first column displays the referenced paper and highlights the related technology, the second column identifies the specific industry/application, the third column

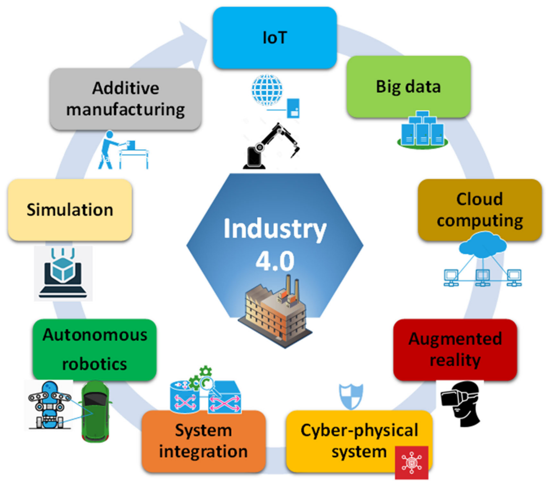


Fig. 2. Key enabling technologies in Industry 4.0.

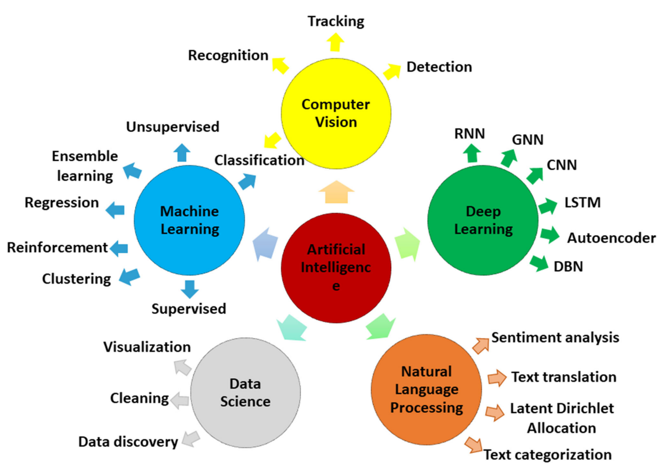


Fig. 3. Main AI-related areas in Industry 4.0.

provides a short description of utilized technology, while the last column gives a contribution summary of the work.

III. Role of AI in Industry 4.0

AI integrates several technologies that enable software, systems, machines, and devices to sense, perceive, develop, understand, and learn from their own experiences or enlarge human activities. With AI, industrial production systems can obtain more extraordinary performance than humans. Additionally, AI can allow robots to complete tasks that a human would not perform, for instance, managing critical or dangerous raw materials or microscopic elements. In this perspective, it is necessary to understand that, at this instant, numerous industrial robots are not that smart as humans. Nevertheless, they can indeed deliver many skillfully jobs in many situations, though they are programmed in a restricted manner. Continuous advancement made evidence that this technology advances with Industry 4.0. Some AI-relevant areas applied in Industry 4.0 are shown in Fig. 3 and discussed as follows: Table II highlights a summary of different AI-related areas, including ML, DL, NLP, and computer vision (CV) applied in other industrial applications. Moreover, we review various methods and algorithms used with different Industry 4.0 enabling technologies.

A. Machine Learning

ML is a subgroup of AI that describes one of the basic principles of AI. It learns from experiences or datasets rather than just instructions. ML-based methods automatically learn and enhance system outcomes by training, e.g., [10]. These methods examine the final output for each recognizable pattern and seek reverse-engineering aspects to provide an output. It develops a system of how to make conclusions and decisions based on previous experiences [11]. ML methods are mainly categorized in unsupervised, supervised, and reinforcement approaches, as shown in Fig. 3. Researchers in [12], utilized data fusion, ML, based methods, e.g., [support vector machine (SVM), DWT transformation, fast Fourier transform, principal component analysis, Gaussian mixture models, K-nearest neighbors (KNN), artificial neural networks (ANNs), for descriptive, predictive, and prescriptive prognostic maintenance and analytics in Industry 4.0. Kucukoglu *et al.* [13] utilized ANN for product failures inspection in Industry 4.0. Cohen *et al.* [14] presented an assembly system using ML and explored its strategic, tactical, and operational levels impacts. Carvajal *et al.* [15] used random forest, gradient boosting, multilayer perceptrons (MLP), and ANN for early detection and product failure in Industry 4.0. Park *et al.* [16] presented a context-aware intrusion detection system using clustering, autoencoder, linear regression, K-mean, random forest, and density-based spatial clustering of applications with noise (DBSCAN) method.

B. Deep Learning

DL is a subset of AI and ML. It directs a system or machine to handle information through layers, to classify, interpret, and predict the outcome. Some mainly utilized DL approaches are convolutional neural networks (CNN), recurrent neural networks (RNN), and generative neural networks (GNN), as shown in Fig. 3. Neural Networks operate nearly on the same principles as human neural cells. A group of methods or algorithms obtains the correlation between different underlying variables and prepares the data as a human brain makes. DL is growing successful as the systems or models can deliver state-of-the-art accuracy. Diez *et al.* [12] utilized DL-based methods, e.g., [RNN, hidden Markov model, RNN, backpropagation neural networks, deep belief networks (DBN)] for descriptive, predictive, and prescriptive maintenance and analytics in Industry 4.0. Researchers in [17] and [18] presented a CNN model for a real-time product inspection system and for early fault detection for manufacturing industries, respectively. In [19], scholars utilized CNN-based model, i.e., LiftingNet, for fault classification and to determine characteristics adaptively from noisy data without previous knowledge. Luo *et al.* [18] presented a DL-based method for immediate fault detection in time-varying situations. Tao *et al.* [20] presented a multilayer gated recurrent unit (MGRU) system for spur gear fault analysis. The evaluation of the classification accuracy of the method is made using long short-term memory (LSTM) and SVM, respectively. Cheng *et al.* [21] introduced a method for predictive maintenance utilizing adaptive kernel

TABLE II
SUMMARY OF DIFFERENT AI AND XAI-BASED METHODS USED IN VARIOUS INDUSTRIAL APPLICATIONS

Broad Area	Application	Technology	Methods/ Models	Main Contribution
ML [10]	Design, Manufacturing Operation	Simulation, Cyber physical system, IoT, Big data analytics	Generic ML algorithm	Data analysis and processing for design improvements of ships manufacturing.
ML [11]	Tracing tracking in production	Cloud computing	Ontology-based Interpretable Model	Product-in-use assessment in Industry 4.0.
ML [22]	Automotive industry	IoT, Cyber physhopsical system	Not Specified	Customized and advanced services Industry 4.0
ML DL [12]	Manufacturing Industry	System integration, IoT	SVM, DWT Transformation, Fast Fourier Transform, FPCA, Gaussian Mixture Models, GRNN, Hidden Markov Model, KNN, RNN, ANNs, DBN	Overview of pescriptive, predictive, and prescriptive prognostic maintenance and analytics in Industry 4.0.
ML [14]	Assembly systems	IoT, Cloud computing , Additive Manufacturing	Autonomous decision using ML	Explore the impact of Industry 4.0 strategic, tactical, operational levels of assembly lines.
ML [15]	Production line failure	IoT, Simulation	Random Forest, Gradient Boosting, MLP, ANN	Presented case study, a real-time early detection and product failure system for Industry 4.0.
ML [16]	Manufacturing Process	IoT, Cyber physical system,	Clustering, Autoencoder, Linear Regression, K-mean, Random Forest, and DBScan	Presented a context-aware intrusion detection system for Industry 4.0.
ML CV [23]	Tracking human	IoT	Feature and Blob based method	Presented a features-based person tracker model for industrial environment.
ML CV [24]	Manufacturing Industry	Big data, IoT	SVM, Decision trees, Random forests, Logistic regression, KNN	Identification and classification of materials in the context of Industry 4.0.
ML [25]	Maintenance Industry	IoT, Cyber physical system	K-means, Gaussian mixture	Presented a real-world implementation cycle, for knowledge discovery using machining learning.
NLP [26]	Human Resource Management	IoT	Text Mining	Presented a tool to automatically determine Industry 4.0 impact on human resource management.
NLP [27]	Supply chain	IoT	Latent Dirichlet Allocation	Multi-tier supply chain in Industry 4.0.
NLP [28]	Industry	IoT	Neural Network	Utilized attention mechanisms, presented a NN based model for the translation of natural language used in SQL database system.
DL [17]	Manufacturing	IoT, Cloud computing	CNN	Presented robust real time product inspection system based on fog computing and DL.
CV DL [29]	Printing Industry	IoT, Cloud computing	DNN	Presented a deep learning based automated Quality Control system for Printing Industry 4.0.
CV DL [30]	Manufacturing	IoT, Cloud computing, Simulation	DBN-DL	Developed and IoT sensor based fault detection system based on deep learning for Industry 4.0.
DL [19]	Fault Detection	IoT	DNN CNN, (LiftingNet)	Presented a DL network for fault classification and to adaptively train features from noisy data without previous knowledge.
DL [18]	Manufacturing	IoT	CNN, Autoencoders	Presented a DL based method for early fault identification in time-varying conditions situations.
ML DL [20]	Manufacturing	IoT	MGRU, LSTM Multilayer LSTM and SVM.	Presented a MGRU method for spur gear fault diagnosis. Evaluation of the methods classification accuracy is made using LSTM, MLSTM, and SVM.
DL [21]	Predictive Maintenance	IoT	AKSC, LSTM-RNN	Presented a novel method using DL, to classify anomaly behaviors from multiple degradation features.
DL [31]	Human Detection	IoT	Faster-RCNN, SSD, YOLOv3	Detecting human in complex industrial environment using different deep learning methods.
ML [32]	Various Industries	Not Specified	Interpretability and explainability ML	Real-world application of explainability methods used for search and recommendation systems. (lending, leasing, sales, and fraud discovery)
DL [33]	DFKI-Smart-Lego-Factory	IoT	Global and Local explanations for process outcome predictions using the applied deep neural network.	Presented a utilization case for DL method for prediction. Illustrated the insights of decision-making and the purpose of the intelligence in Industry 4.0.
ML [34]	Anomaly Detection	Big data, IoT	Explainable Feature importance Isolation forest algorithm.	Introduced a method for determining a feature importance in Anomaly identification in Industry 4.0.
ML [35]	Condition-based monitoring, predictive maintenance,	IoT, Cyber physical system, Cloud computing	Explainable ML quantitative association rule mining.	Explainable and Predictive model for IoT applications in Industry 4.0
XAI ML [36]	Manufacturing System Operations	IoT, Cyber physical system,	Visualization and Explainable ML.	Presented visual features of real-time predictive analytics and multivariate time series method to highlight possible errors, warnings, and malicious intrusions attacks.
XAI ML DL [37]	Anomalous behavior prediction	IoT	Explainable interpretable regularize logistic regression, Feature extraction (shape based, direct, CNN, RNN, and selection (Kolmogorov–Smirnov (KS))	Introduced Interpretable Anomaly Prediction model for Industry 4.0. Identify anomalies in the current data and also be able to predict it probability in the future data.
XAI [38]	Smart Industries	IoT, Cyber physical system	Integration of meta learning and AI based approaches	Implement integration of XAI methods and Deep meta-learning paradigms for Cyber physical systems.

spectral clustering (AKSC) and LSTM-RNN for classification of anomalous behaviors using multiple degradation features.

C. Natural Language Processing (NLP)

NLP is a science of understanding, interpreting, reading a language by a system or machine. Once a system knows what the user means to communicate, it works appropriately. An element of AI, NLP, is a system's or machine's ability to learn, perceive, and understand the human language as it is delivered. The goal of NLP is to recognize and understand the human language to present a result conclusively. Most NLP methods nowadays use ML and DL-based techniques to extract insights from human language. Such as Zhou *et al.* [27] studied an NLP-based method named Latent Dirichlet Allocation for multitier supply chain in industrial application. Authors in [28] presented a neural network-based model using attention mechanisms for the interpretation of natural language in english to structured query language (SQL). It is used in an SQL database system for storing data from various devices and sensors in Industry 4.0.

D. Computer Vision

CV is an area of research where systems are produced empowering computers to "see" interpret and understand digital videos and images. Its goal is to make conclusions from visual references and utilize them to solve real-world problems. Currently, there are several applications of CV, and the future continues an enormous scope. Various industrial organizations use computer vision for fault detections, the financial institution used it for, fraud prevention, allow mobile deposits, and display information visually, e.g., [19], [30], [18]. Penumuru *et al.* [24] utilized computer vision-based identification and classification of materials in the context of Industry 4.0. Villalba-Diez *et al.* [29] presented DL-based automated quality control system for image classification in the printing industry. Lee [30] presented a computer vision and DBN-DL based fault detection and classification system for the manufacturing industry.

IV. XAI in Industry 4.0

AI-based methods are growing more precisely, more explanations or information to the specialists about how the decisions and instructions are necessary. Thus, decisions must be understandable and explainable for a smooth deployment of the AI systems and their acceptance or adoption by the specialists. Explainability is known as a means to enhance user trust in the models. Although explainability is not a precisely specified term: it includes various aspects, dimensions, and aims. For example, nature and sufficiency broadly depend on the specific context of the opinion and the user's properties. Decisions from the cognitive analysis verify that while understanding the intrinsic mechanisms of ML and deep learning models for data specialists/scientists is fundamental, it is also described by significant cognitive stress indeed to the extent of extreme applications. Several techniques have been introduced in the literature to analyze explainability models [46], [47]. Usually, the classification methods are not perfect; they extensively, depending upon the methods' components, can vary and be divided into different kinds, i.e., overlapping or nonoverlapping kinds. Some methods shown in Fig. 4 are explained shortly here, and a comprehensive review can be found in [48]. XAI enables humans to recognize, learn, understand, interpret, and articulate how an AI model or system concludes and makes decisions. Table III provides a summary of various XAI-based methods or approaches used in various industrial applications along with Industry 4.0 enabling technologies.

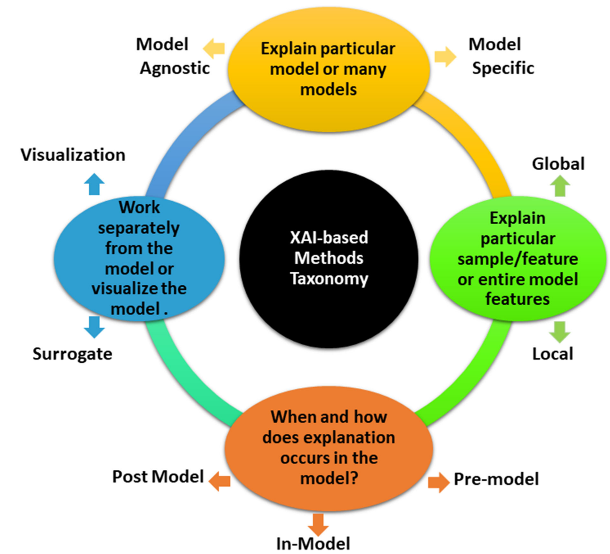


Fig. 4. Overview of XAI-based approaches.

A. Model-Specific and Model Agnostic Approaches

These approaches to explanations are presented and applied to understand the decisions of ML and DL-based methods. Model-specific approaches depend upon the parameters of the specific methods or models, e.g., decision tree, SVM, random forest, linear regression, eXtreme gradient boosting (XGBoost) classification algorithm [39], graph neural network explainer [49] is a kind of this interpretability where the complex structure of data requires precise knowledge of the models. Model Agnostic approaches are principally suitable in the posthoc interpretations and not restricted to fixed systems or model structures. These approaches do not produce immediate access or path to the central model weights or architectural parameters, e.g., partial dependency plots, local interpretable model-agnostic explanations (LIME) [50], [40] and quantitative association rule mining [35]. Carletti *et al.* [34] utilized these methods for anomaly detection and decision making in industry 4.0.

B. Local and Global Approaches

Local interpretable approaches are suitable to a particular result of the system. It can be achieved by describing mechanisms that specify the reason and purpose for a special prediction or result. For instance, a model or system is interested in special characteristics and features. It provides explanations related to individual predictions. In contrast, global approaches focus on the core of systems and models by applying the model's complete knowledge, learning, and correlated data. It seeks to define the nature, behavior, and performance of the model in common. Feature importance is an excellent illustration of this approach that investigates to find the features or characteristics

TABLE III
SUMMARY OF VARIOUS AI AND XAI BASED METHODS USED IN VARIOUS INDUSTRIAL APPLICATIONS

Broad Area	Application	Technology	Methods/ Models	Main Contribution
XAI ML [39]	Business	IoT	Visualization and ML (Shapley values, XGBoost predictive classification algorithm.)	Proposed an XAI model that can be applied to justify why a customer buys or leaves non-life insurance coverage.
XAI ML [40]	Industrial machinery	IoT	Visualization and ML techniques local and global explanations, Random forest, ELI5 and LIME.	Implementation and explanations of a residual life estimator design based on machine learning employed to industrial data.
XAI [41]	Manufacturing	IoT	Visualization Nonlinear modeling with SHAP values data-driven decision model. [41]	Proposed a data-driven decision model to improve process quality in manufacturing by combining nonlinear modeling and SHAP values from the field of explainable AI.
XAI DL [42]	Manufacturing	IoT	XAI methods Smoothed Integrated Gradients, Guided Gradient Class Activation Mapping DeepSHAP CNN classifier.	Presented a DL based classification method for fiber layup fault identification in the automatic composite manufacturing.
XAI DL [43]	Predictive Process	IoT	Local post-hoc explanation DL, Surrogate (Decision tree)	Introduced a new local post-hoc explanation method for monitoring problems in the predictive process.
XAI [44]	Fault Detection Diagnosis	IoT	Unsupervised classification, SHAP and Local Depth-based Feature Importance Isolation Forest (Local-DIFFI).	Presented a fault diagnosis and anomaly detection techniques in rotating machinery to interpret black-box models.
XAI DL [45]	Manufacturing	IoT	Synthetic Minority Oversampling Technique (SMOTE), Random forest and association Rule Mining, Lightweight on-line detector of anomalies, Minimum Covariance Determinant PCA, t statistic.	Presented an XAI-based method for fault analysis and penetration harvesting for steel plates manufacturing.

that are generally responsible or answerable for the model's more reliable performance amongst all distinct features [34]. It explains the complete predictive model to the user and helps them to interpret and understand the decision. Rehse *et al.* [33] presented the IoT-based system utilizing global and local explanations for process result predictions using the deep neural network. Serradilla *et al.* [40] used random forest, explain like I'am 5 (ELI5), and LIME explainable methods to make local and global explanations for life estimator models based applied to industrial data.

C. Premodel, In-Model, and Postmodel Approaches

Premodel approaches are usually autonomous and do not depend upon a specific model or system architecture to apply it. Common examples of these approaches are principal component analysis and t-distributed stochastic neighbor embedding [45]. Interpretability systems, itself combined into the model and described as in-model approaches like association rule mining [45]. Different approaches are executed after making a system or model, and therefore, these techniques are named postmodel approaches. These approaches are capable of probably producing important penetrations regarding what precisely a system or model learned throughout the training, for example, SHapley Additive exPlanations (SHAP) values data-driven decision model [51], [41], [44]. Langone *et al.* [37] utilized these approaches to identify anomalies in the current data and also able to predict its probability in the future data. Mehdiyev *et al.* [43] utilized local posthoc explanation method using DL for monitoring problem of predictive process.

D. Visualization and Surrogate Approaches

The visualization approaches are not a distinct model, although they describe some components of the models or systems by visual perception, such as activation maps. The basic concept is to understand ML and deep learning models, specifically to visualize their representations to explore and analyze the hidden patterns inside a neural unit. It is noticed that these analysis techniques are nonrestrictive and based upon various reasonable intuitions and, thus, have considerable overlaps. For instance, mostly the posthoc models or systems like attributions might be observed as model agnostic as such approaches are often not vulnerable to a system's or model's architecture. Le *et al.* [36] presented visual features of real-time predictive analytics and multivariate time series method to highlight possible errors, warnings, and malicious intrusions in Industry 4.0. Garmegna *et al.* [39] employed visualization and ML methods (Shapley values, XGBoost predictive classification algorithm) to justify why a consumer buys or drops a nonlife insurance coverage. In [41] Senoner *et al.* utilized nonlinear visualization model SHAP values with a data-driven decision model to improve process quality in manufacturing. Surrogate approaches involve various models as a collection, applied to evaluate different black-box models. These models can be interpreted further by understanding the model's conclusions and by examining the decision of the black-box model and surrogate model. Mehdiyev *et al.* [43] utilized the surrogate method (decision tree) for predictive process monitoring problem.

V. INTEGRATION OF AI AND XAI-BASED METHODS IN INDUSTRY 4.0 APPLICATIONS

Technologies associated with Industry 4.0 integrated with advanced AI and XAI-based methods achieve remarkable success, accuracy, and quality in different applications. Explainable and interpretable architectures can achieve a great level of abstraction by using high data samples, thus gaining great attention in all fields of Industry 4.0. Some applications of AI and XAI-based methods and approaches are explained in Table IV. The Table summarized the key enabling technologies and various methods along with their specified area applications.

A. Smart Cities

Intelligent cities are frameworks or structures predominantly made up of communication, information, and technologies, in

TABLE IV
APPLICATIONS OF AI AND XAI-BASED METHODS COMBINED WITH INDUSTRY 4.0

Application	Specific Area	Technology	Contribution Summary
Smart Cities	Various applications [52]	IoT, Cyber physical system	Discussed the concept of Industry 4.0 for smart cities applications.
	Different smart applications [53]	Information Communication Technologies	Provided a global perspective of smart cities applications.
	AI based applications [54]	IoT, Big data	Discussed various applications of Big data and AI in smart cities.
	Flood monitoring [55]	IoT	Developing smart cities with XAI.
Smart factories	Energy production and management [56]	IoT	Presented a conceptual IoT-based method for smart factories in Industry 4.0.
	Manufacturing [57]	Digital technologies	Smart factories using Industry 4.0.
	Manufacturing[58]	Cloud computing	Presented a Cloud computing and AI based method for manufacturing in smart factories.
	Manufacturing [33]	IoT	Explainable process predictions for Industry 4.0.
Smart Healthcare	Medical [59]	IoT	Review various applications of Industry 4.0 in Healthcare.
	Medical [60]	IoT, Big data	Reviews AI, IoT and wearble devices in smart Healthcare.
	Health condition monitoring[61]	IoT	Analysis and Diagnosis of healthcare data with Explainable AI.
Human Computer Interaction	Manufacturing and Industry [62]	IoT, Cyber physical system, Augmented reality	Provided state of the art human computer interaction applications in Industry 4.0.
	Healthcare [63]	IoT	AI (DL, CV) and XAI for Human Computer Interaction
Predictive Maintenance	Fault detection[64]	IoT, Cyber physical system	Predictive maintenance for fault prognosis and diagnosis in Industry 4.0.
	Condition monitoring [65]	IoT	Machine Learning for predictive maintenance in Industry 4.0.
	Production management [66]	IoT	AI and XAI based model for prediction of errors and tool failures in Industry 4.0.
Smart Assistance	Demand forcasting in manufacturing [67]	IoT	Demonstrated a system for demand forecasting use in manufacturing.
Smart products	Development [68]	IoT, Cyber physical system, Augmented reality	Review of developments approaches of smart products used in Industry 4.0
	Manufacturing [69]	IoT	Provided a survey of various implementation technologies used in Industry 4.0 by manufacturing companies .
	Development [70]	IoT, Cyber physical systems	Review trends of emerging technologies for smart product development.
Industrial Robots	Augmented reality [71]	IoT, Cyber physical system, Augmented reality	Implementation of augmented reality to analyze and estimate the usage of a production and industrial robot.
Cyber security and privacy	General industry [72]	IoT, Cyber physical system	Presented an overview of Cyber security threats in Industry 4.0.
	Monitoring and identification [73]	IoT, Cyber physical system	AI based framework for Cyber security and privacy.
	Intrusion and threat detection [74]	IoT, Cyber physical system	A survey on AI for Cyber security and threats
Smart Transportation	Traffic surveillance [52]	IoT	CV, AI applications of Industry 4.0. Presented a multicamera solution for traffic monitoring.
	Smart lighting and Smart Parking [75]	IoT	AI and Video analytics based system for smart Transportation
	Transportation [76]	IoT	Reviewer of ML and IoT for smart transportation.
Autonomous vehicles	Cyber attacks [77]	IoT	Autonomous vehicles in the era of Industry 4.0. Analyze threat classification in autonomous vehicles, utilizing accountability, authentication, and service availability.
Chatbots	Human chatbot communication [78]	Robotics	AI for human to human and human to chatbot conversations.
Autonomous Resource exploration	Autonomous Exploration and Mapping System[79]	Emerging technologies	Autonomous exploration and mapping systems
Augmented reality	Human robot collaboration [4]	IoT, Augmented reality, Autonomous robotics	Augmented reality applications in Industry 4.0

which metropolitan planning and sustainable developing processes are established and carried out to give rising demands of urbanization. IoT applications are based on an intelligent network of connected devices, objects, sensors, systems, and machines that transmit data using wireless technology and cloud, backed by big data [52]. Smart cities utilize this data to achieve standards that enhance the inhabitants' effectiveness and quality of living. Smart city application involves the smart environment, smart systems, or solutions for controlling environmental conditions, irrigation, photovoltaics, waste, lighting, water supplies, and weather station [53]. It aims to increase energy performance and the nature of the environment in cities. It also performs an essential role in smart mobility [80] consists of smart monitoring methods for pedestrians, parking spaces, bike lanes, capacity control, traffic control, charging stations, and tourist saturation. Furthermore, it aims to overcome the noise of cities so that they can move normally. Another aspect is smart living, consisting of smart fire detection systems, air conditioning, video surveillance, and home sports facilities. Its purpose is to enhance the quality of living. Additionally, it represents an essential role for citizens as smart people, consisting of optimizing their services. These solutions link informational mupis, citizen apps, citizen cards, and social Wi-Fi to enhance interaction between the various parties.

B. Smart Factories

Industry 4.0 has been making factories transformed as the later industrial innovation promises to give a more active, flexible, connected, and responsive manufacturing and related industries [56]. There are enough new features to be examined from the IoT to AI when promoting smart factories [57]. Smart factories successfully established a digital transformation and can create and promote their datasets to implement AI and XAI to enhance quality management, regularity, and maintenance by developing predictive studies of equipment functionality and completely streamlining factory boundaries. While the advantages of AI are popular when it applies to production processes, it is necessary to identify that factories should have an AI and XAI development plan and a scheme to the type of industrialization and automation platform to apply. The introduction of IoT devices, big data and cloud computing, and cyber-physical systems in the factories is the most efficient method to transform smart factories in Industry 4.0.

C. Smart Manufacturing

Industry 4.0 advances manufacturing factories more intelligent, adaptable, and productive by implementing and equipping them with smart sensors, devices, and independent, autonomous systems [81]. Consequently, machines, systems, and equipment produce high standards of self-optimization and industrialization. Furthermore, the manufacturing process involves the capability to fulfil further complex and efficient specifications and conditions of products, as expected [82]. Therefore, smart factories and smart manufacturing are the principal targets of Industry 4.0. When implemented with the appropriate approach, AI and XAI have numerous benefits for the manufacturing industry, including error reduction (intelligent algorithms can perform tasks and reduce susceptibility to errors in processes executed by humans), cost reduction (various e-commerce shops) banks are utilizing robots to begin consumer assistance. In this way, organizations can decrease employee expenses or assign them to other jobs in more imperative and complex fields that can enhance profit and concentration on their job.

D. Smart Healthcare

Industry 4.0 presents the comprehensive ability to manufacture newly customized systems, innovative devices, and healthcare field tools. It gives a special kind of digital hospital and a perfect monitoring system that satisfies the patient/pharmaceutical industry's specific requirements with optimized circumstances and expense. The application of IoT, cloud computing, and big data generates a modern smart healthcare sector. It builds connectivity of data with the aid of IoT, innovative manufacturing technologies, software, devices, robots, sensors, and other high-level information technologies [59] Advancement in information and communication technology improves healthcare quality, changing traditional healthcare organizations into smart healthcare. Smart healthcare is a health maintenance system that utilizes technology such as wearable sensors, IoT, and portable Internet to obtain information dynamically, connect people, elements, and organizations associated with healthcare, and later actively controls and effectively responds to pharmaceutical ecosystem demands [60]. Smart health care's key concept includes electronic health assistance, computerized record supervision, noninvasive services, and smart and connected pharmaceutical devices and sensors. AI and XAI-based methods [61] save pharmaceutical staff time, enabling them to concentrate on the interpretive performance of medication rather than repetitive tasks.

E. Human–Computer Interaction (HCI)

This section discusses the ways people can interact with a machine and systems. In Industry 4.0, improved and developed HCI or human–machine interaction tries to answer the question: how can people communicate with machines such as devices, robots, data, and services? It mainly concentrates on the design, evaluation, and application of communication and information technologies, including with a specific aim to enhance user practices, task execution, and quality of experience [62]. HCI is recently being developed and growing using AI and XAI applications, [83], [63] thus heading to the fast evolution of innovative and interesting research areas. AI and XAI aim to provide, develop, promote, and explore novel methodologies and empirical insights related to HCI events, including but not confined to m-commerce, e-commerce, employment, companies, human interactions with smart machines, technologies, human–robot interactions, innovative interface configurations for augmented reality, virtual reality and analysis of HCI problems within neuro-physiological devices, machines, and tools (e.g., CT-Scan, EEG, MRI, GSR, and eye-trackers).

F. Predictive Maintenance

Advancement in communication and information technologies changing manufacturing industries for a smarter approach, continuously examining performance data to notify actionable penetrations that predict product malfunction, improve up-time and increase asset productivity [64]. In predictive maintenance, information is gathered in real time to control the status of devices. The aim is to discover patterns that can assist in predicting and eventually anticipate malfunctions; frequently, within training methods, AI methods [65] are practiced to accomplish this aim. When predictive maintenance is computerized, systems become more imperative when establishing devices' requirements and predicting if maintenance should be completed. Admittedly, the implementation of AI and XAI-based methods [66] head to significant price savings, longer predictability, and the expanded availability of the systems.

G. Smart Assistance

AI and XAI enable machines and devices to understand voice, speech, or text information and, thus, react according to it with the corresponding application. These are preprogrammed systems that operate under ML, DL, NLP, AI, and XAI. Smart robots, devices, systems, and tools are produced in such a way that they can accomplish particular jobs that need human intelligence or the human brain [67].

H. Smart Product

Smart products in Industry 4.0 utilize IoT, cloud computing, cyber-physical systems, AI, and XAI-based methods that allow humans to interact with products [68]. The current production methods require to be combined with Industry 4.0, which allows innovative technologies for product advancement. It includes advanced, improved automatic experience, knowledge, and real-time applied production systems. Therefore, intelligent products require to be designed with powerful technologies in intertwined digital and environmental methods. IoT, big data, cloud computing, volume customization, and production time development are operators that control and manage the advancement of Industry 4.0 [69].

I. Industrial Robotics

Advanced AI and XAI methods enable the industrial robot to operate and control robots in different industries automatically. Typical applications involve welding, ironing, painting, equipment, place and pick, palletizing, product investigation, and experimentation, all performed with high strength, velocity, and accuracy. Technologies associated with Industry 4.0, such as augmented reality [71].

J. Cyber-Security and Privacy

The combination of information and communication technology begins with new challenges, especially cyber-security. The existence of the IoT has also greatly remodeled the presence of cyber threats. Security threats and vulnerabilities of IoT create technical hurdles, main causes for cyber-attacks, cyber-security requirements, and methods with a global perspective, including private and public division. AI determine cyber-security and privacy aspects such as cyber threat detection in smart network systems of Industry 4.0 [73], [74]. It usually involves examining the network infrastructure and identifying threats of cyber-attacks in real time. It also often includes network traffic investigation, endpoint detection, acknowledgement, and malware detection. AI-enabled cyber threat detection systems are usually components of a more comprehensive cyber-security solution that further utilizes many prevention measures (e.g., firewalls).

K. Smart Transportation

The transportation field also improves rapidly with the emergence of Industry 4.0 [52]. Smart technology assists determined transportation time on the road or gives recommendations for further effective means of transportation, alternative route plans, identification of traffic signs, autonomous or self-driving vehicles, and sensors. AI-based methods [75] also enhanced transportation capabilities by using advanced computer vision-based systems for automated detection and tracking of vehicles. IoT, cloud computing, and big data advancement also improve transportation services [76].

VI. Discussion and Future Trends

The abovementioned literature review assessed that AI and XAI-based methods combined with Industry 4.0 achieved notable progress in different fields. AI-based systems, including ML, DL, NLP, and CV, are extensively applied in different applications, with IoT, big data, cloud computing, cyber-physical systems, and intelligent network architectures. Furthermore, advanced communication and information technologies with AI and XAI-based systems can support the development of intelligent and innovative system-based applications and digital twin technology to test those systems before implementation. Industry 4.0 is now a reality for a vast number of industries worldwide. Although it still requires improvements to obtain the advances that may revolutionize all sectors, it can be considered an open-ended method that is progressively evolving.

In this perspective, AI can be considered one of the most prominent elements of the Industry 4.0 revolution. However, AI methods still suffer from many challenges. Indeed, primarily AI-based systems, methods, and algorithms are power-hungry and need an ever-increasing quantity of cores and GPUs to work effectively. Another significant challenge to be considered is the unknown nature of AI-based methods: how do ML and DL models predict the output? It is also challenging and demanding for researchers to get the human-level accuracy of such systems. Furthermore, AI methodologies often need the following:

1) hyperparameters optimization;
2) finetuning;
3) huge datasets;
4) robust computing capability;
5) continuous training on data.

Hence, all the ML and DL models are based on a key aspect that is the data and resources availability. Such data are usually collected and generated from millions of sources, devices, and users; there are also chances that personal or sensitive data can be affected due to cyber-attacks. The bias nature of the data also affects the performance of the AI-based system in real-time applications. Thus, the intrinsic quality of AI requires the obvious explanation that XAI might give to a system that enables human-level intelligence.

Explainability is one of the emerging and effective areas supporting AI; it is an essential set of methodologies that can provide insights beyond what was not achievable with conventional linear models. The XAI-based models can improve the trust and transparency of the models; however, many challenges still need to be addressed. The developed models do not ensure that the system has been trained on true or unbiased data set (how the dataset is obtained and created), leading to vulnerabilities of the training phase, design, model, and objective function. We have discussed various XAI-based methods, but we cannot ensure the confidential level of any model that would be a security risk.

Similarly, sometimes developed systems, algorithms, and models are well understood but, at the same time, are highly complex. Thus, a layman or industry needs a clear and precise understanding that is irrational. It is an extent to which XAI methods may be beneficial since XAI can design alternative systems, models, and algorithms that are easier to explain. The developed algorithms and models sometimes use legitimate and authentic data to produce predictions and make decisions that are not consistent, reasonable, biased, or out of sequence sometimes. Reasonableness is relevant and has an alternative viewpoint of contingent against the particular information given at the input to the AI algorithms and models. It does not ensure that the output predictions and decisions are adequate if based on an AI system. In some applications, we may explain how an algorithm, model, and system is working; but, we require clarification and explanation for how the system is compatible and consistent with a moral and legal code.

Technological advancements and inventions have consistently influenced us; currently, the most significant improvement in history is the revolution of Industry 4.0 along with AI. The growth rate of Industry 4.0 with AI and other technological advancements, including the Internet, industry, manufacturing, digitization, is nowadays overwhelming. Such progress will continuously grow as an industry innovator for the predicted future. Therefore, AI and XAI emerged as significant concerns in the industry realm. Various industries over the globe are turning up with important innovations in AI and XAI. These technologies and methods impact the future of all industries and humans and are additionally developed as emerging technologies such as big data, smart cities, manufacturing, education, factories, healthcare, augmented reality, robotics, and IoT. As these technologies continue to grow, they will influence the social context and quality of life in the future. XAI systems can enhance the automatic learning of techniques that might help to improve the quality of the product by advancing predictive maintenance systems into production methods, substituting visual investigations with robots or cobots that perform quality checks more accurately and effectively. XAI and its use in Industry 4.0 can improve applications, and digital transformation adoption help them to adjust according to growing future consumer demands. With intelligent manufacturing that is the backbones of the world economy, the technology implementation in this area is all about unleashing the typical potential of products and explanations for the consumers in the future. Therefore, analytics and IoT can perform a considerable role in Industry 4.0, recognizing patterns and behaviors and delivering real-time data to related industries and manufacturers' fingerprints. XAI-based method, along with key enabling technologies, can also be utilized in the health monitoring application, e.g., for the analysis and prediction of pandemic situation COVID-19 [84].

VII. Conclusion

Industry 4.0 represents a modern automation and data communication paradigm in manufacturing and related industries. It connects technologies, including cyber-physical systems, big data analytics, IoT, cloud computing, many others, and develops smart, practical applications. This article provided a comprehensive survey of AI and XAI-based methods applied in different Industry 4.0 contexts. We have discussed the key technologies enabling Industry 4.0, also presenting an in-depth investigation of different AI and XAI-based methods combined with Industry 4.0. Such a paradigm can also be supported by evaluating big data analytics, improving the collection and analysis of data in different industrial applications. During this revolution, new advanced systems have been developed, and they can continuously adapt to the industrial changes. We concluded that AI and XAI enable automatic and real-time implementation of these intelligent systems and applications. Therefore, AI is the main component of industrial transformation that empowers smart machines to execute tasks autonomously, while XAI develops a set of mechanisms that can produce human-understandable explanations. We also discussed how, why, and where such approaches have been used with Industry 4.0. Finally, opportunities and challenges and future research directions have been addressed for further improvements and developments of the Industry 4.0 revolution.

References

[1] E. Oztemel and S. Gursev, "Literature review of Industry 4.0 and related technologies," *J. Intell. Manuf.*, vol. 31, no. 1, pp. 127–182, 2020.

[2] S. F. Wamba, S. Akter, A. Edwards, G. Chopin, and D. Gnanzou, "How 'Big Data' can make big impact: Findings from a systematic review and a longitudinal case study," *Int. J. Prod. Econ.*, vol. 165, pp. 234–246, 2015.

[3] J. H. Kim, "A review of cyber-physical system research relevant to the emerging it trends: Industry 4.0, IoT, big data, and cloud computing," *J. Ind. Integration Manage.*, vol. 2, no. 3, 2017, Art. no. 1750011.

[4] F. De Pace, F. Manuri, and A. Sanna, "Augmented reality in Industry 4.0," *Amer. J. Comput. Sci. Inf. Technol.*, vol. 6, no. 1, p. 17, 2018, doi: 10.21767/2349-3917.100017.

[5] Y. Lu, "Cyber physical system (CPS)-based Industry 4.0: A survey," *J. Ind. Integration Manage.*, vol. 2, no. 3, 2017, Art. no. 1750014.

[6] U. M. Dilberoglu, B. Gharehpapagh, U. Yaman, and M. Dolen, "The role of additive manufacturing in the era of Industry 4.0," *Procedia Manuf.*, vol. 11, pp. 545–554, 2017.

[7] M. A. K. Bahrin, M. F. Othman, N. H. N. Azli, and M. F. Talib, "Industry 4.0: A review on industrial automation and robotic," *Jurnal Teknologi*, vol. 78, pp. 6–13, 2016.

[8] M. Ghobakhloo, "The future of manufacturing industry: A strategic roadmap toward Industry 4.0," *J. Manuf. Technol. Manage.*, vol. 29, no. 6, pp. 910–936, 2018.

[9] J. Qin, Y. Liu, and R. Grosvenor, "A categorical framework of manufacturing for Industry 4.0 and beyond," *Procedia Cirp*, vol. 52, pp. 173–178, 2016.

[10] J. H. Ang, C. Goh, A. A. F. Saldivar, and Y. Li, "Energy-efficient through-life smart design, manufacturing and operation of ships in an Industry 4.0 environment," *Energies*, vol. 10, no. 5, p. 610, 2017.

[11] A. Bougdira, I. Akharraz, and A. Ahaitouf, "A traceability proposal for Industry 4.0," *J. Ambient Intell. Humanized Comput.*, pp. 1–15, 2019.

[12] A. Diez-Olivan, J. Del Ser, D. Galar, and B. Sierra, "Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0," *Inf. Fusion*, vol. 50, pp. 92–111, 2019.

[13] I. Kucukoglu, H. Atici-Ulusu, T. Gunduz, and O. Tokcalar, "Application of the artificial neural network method to detect defective assembling processes by using a wearable technology," *J. Manuf. Syst.*, vol. 49, pp. 163–171, 2018.

[14] Y. Cohen, H. Naseraldin, A. Chaudhuri, and F. Pilati, "Assembly systems in Industry 4.0 era: A road map to understand assembly 4.0," *Int. J. Adv. Manuf. Technol.*, vol. 105, no. 9, pp. 4037–4054, 2019.

[15] J. C. Soto, F. Tavakolizadeh, and D. Gyulai, "An online machine learning framework for early detection of product failures in an Industry 4.0 context," *Int. J. Comput. Integr. Manuf.*, vol. 32, nos. 4/5, pp. 452–465, 2019.

[16] S.-T. Park, G. Li, and J.-C. Hong, "A study on smart factory-based ambient intelligence context-aware intrusion detection system using machine learning," *J. Ambient Intell. Humanized Comput.*, vol. 11, no. 4, pp. 1405–1412, 2020.

[17] L. Li, K. Ota, and M. Dong, "Deep learning for smart industry: Efficient manufacture inspection system with fog computing," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4665–4673, Oct. 2018.

[18] B. Luo, H. Wang, H. Liu, B. Li, and F. Peng, "Early fault detection of machine tools based on deep learning and dynamic identification," *IEEE Trans. Ind. Electron.*, vol. 66, no. 1, pp. 509–518, Jan. 2019.

[19] J. Pan, Y. Zi, J. Chen, Z. Zhou, and B. Wang, "Liftingnet: A novel deep learning network with layerwise feature learning from noisy mechanical data for fault classification," *IEEE Trans. Ind. Electron.*, vol. 65, no. 6, pp. 4973–4982, Jun. 2018.

[20] Y. Tao, X. Wang, R.-V. Sánchez, S. Yang, and Y. Bai, "Spur gear fault diagnosis using a multilayer gated recurrent unit approach with vibration signal," *IEEE Access*, vol. 7, pp. 56880–56889, 2019.

[21] Y. Cheng, H. Zhu, J. Wu, and X. Shao, "Machine health monitoring using adaptive kernel spectral clustering and deep long short-term memory recurrent neural networks," *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 987–997, Feb. 2019.

[22] P. Fraga-Lamas and T. M. Fernández-Caramés, "A review on blockchain technologies for an advanced and cyber-resilient automotive industry," *IEEE Access*, vol. 7, pp. 17578–17598, 2019.

[23] I. Ahmed, A. Ahmad, F. Piccialli, A. K. Sangaiah, and G. Jeon, "A robust features-based person tracker for overhead views in industrial environment," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1598–1605, Jun. 2018.

[24] D. P. Penumuru, S. Muthuswamy, and P. Karumbu, "Identification and classification of materials using machine vision and machine learning in the context of Industry 4.0," *J. Intell. Manuf.*, pp. 1–13, 2019.

[25] J. Diaz-Rozo, C. Bielza, and P. Larrañaga, "Machine learning-based CPS for clustering high throughput machining cycle conditions," *Procedia Manuf.*, vol. 10, pp. 997–1008, 2017.

[26] S. Fareri, G. Fantoni, F. Chiarello, E. Coli, and A. Binda, "Estimating Industry 4.0 impact on job profiles and skills using text mining," *Comput. Ind.*, vol. 118, 2020, Art. no. 103222.

[27] R. Zhou, A. Awasthi, and J. Stal-Le Cardinal, "The main trends for multi-tier supply chain in Industry 4.0 based on natural language processing," *Comput. Ind.*, 2020, Art. no. 103369.

[28] S. Ferreira, G. Leitão, I. Silva, A. Martins, and P. Ferrari, "Evaluating human-machine translation with attention mechanisms for Industry 4.0 environment SQL-based systems," in *Proc. IEEE Int. Workshop Metrology Ind. 4.0 IoT*, 2020, pp. 229–234.

[29] J. Villalba-Diez, D. Schmidt, R. Gevers, J. Ordieres-Meré, M. Buchwitz, and W. Wellbrock, "Deep learning for industrial computer vision quality control in the printing Industry 4.0," *Sensors*, vol. 19, no. 18, 2019, Art. no. 3987.

[30] H. Lee, "Framework and development of fault detection classification using IoT device and cloud environment," *J. Manuf. Syst.*, vol. 43, pp. 257–270, 2017.

[31] I. Ahmed, M. Anisetti, and G. Jeon, "An IoT-based human detection system for complex industrial environment with deep learning architectures and transfer learning," *Int. J. Intell. Syst.*, 2021, doi: 10.1002/int.22472.

[32] K. Gade, S. Geyik, K. Kenthapadi, V. Mithal, and A. Taly, "Explainable AI in industry: Practical challenges and lessons learned," in *Proc. Companion Proc. Web Conf.*, 2020, pp. 303–304.

[33] J.-R. Rehse, N. Mehdiyev, and P. Fettke, "Towards explainable process predictions for Industry 4.0 in the dfki-smart-lego-factory," *KI-Künstliche Intelligenz*, vol. 33, no. 2, pp. 181–187, 2019.

[34] M. Carletti, C. Masiero, A. Beghi, and G. A. Susto, "Explainable machine learning in Industry 4.0: Evaluating feature importance in anomaly detection to enable root cause analysis," in *Proc. IEEE Int. Conf. Syst., Man Cybernet.*, 2019, pp. 21–26.

[35] I. T. Christou, N. Kefalakis, A. Zalonis, and J. Soldatos, "Predictive and explainable machine learning for industrial Internet of Things applications," in *Proc. 16th Int. Conf. Distrib. Comput. Sensor Syst.*, 2020, pp. 213–218.

[36] D. D. Le, V. Pham, H. N. Nguyen, and T. Dang, "Visualization and explainable machine learning for efficient manufacturing and system operations," 2019.

[37] R. Langone, A. Cuzzocrea, and N. Skantzos, "Interpretable anomaly prediction: Predicting anomalous behavior in Industry 4.0 settings via regularized logistic regression tools," *Data Knowl. Eng.*, vol. 130, 2020, Art. no. 101850.

[38] E. Daglarli, "Explainable artificial intelligence (XaI) approaches and deep meta-learning models for cyber-physical systems," in *Proc. Artif. Intell. Paradigms Smart Cyber-Phys. Syst.*, 2021, pp. 42–67.

[39] A. Gramegna and P. Giudici, "Why to buy insurance? an explainable artificial intelligence approach," *Risks*, vol. 8, no. 4, p. 137, 2020, doi: 10.3390/risks8040137.

[40] O. Serradilla, E. Zugasti, C. Cernuda, A. Aranburu, J. R. de Okariz, and U. Zurutuza, "Interpreting remaining useful life estimations combining explainable artificial intelligence and domain knowledge in industrial machinery," in *Proc. IEEE Int. Conf. Fuzzy Syst.*, 2020, pp. 1–8.

[41] J. Senoner, T. Netland, and S. Feuerriegel, "Using explainable artificial intelligence to improve process quality: Evidence from semiconductor manufacturing," *Manage. Sci.*, vol. 224, no. 1, Nov. 2021, Art. no. 109160.

[42] S. Meister, M. Wermes, J. Stüve, and R. M. Groves, "Investigations on explainable artificial intelligence methods for the deep learning classification of fibre layup defect in the automated composite manufacturing," *Composites Part B: Eng.*, 2021, Art. no. 109160.

[43] N. Mehdiyev and P. Fettke, "Explainable artificial intelligence for process mining: A general overview and application of a novel local explanation approach for predictive process monitoring," *Interpretable Artif. Intell.: Perspective Granular Comput.*, Springer, Cham, vol. 937, p. 1, 2021, doi: 10.1007/978-3-030-64949-4_1.

[44] L. C. Brito, G. A. Susto, J. N. Brito, and M. A. Duarte, "An explainable artificial intelligence approach for unsupervised fault detection and diagnosis in rotating machinery," *Mech. Syst. Signal Process.*, vol. 163, 2022, Art. no. 108105.

[45] A. Kharal, "Explainable artificial intelligence based fault diagnosis and insight harvesting for steel plates manufacturing," 2020, *arXiv:2008.04448*.

[46] G. Stiglic, P. Kocbek, N. Fijacko, M. Zitnik, K. Verbert, and L. Cilar, "Interpretability of machine learning-based prediction models in healthcare," *Wiley Interdiscipl. Rev.: Data Mining Knowl. Discov.*, vol. 10, no. 5, 2020, Art. no. e1379.

[47] V. Arya *et al.*, "One explanation does not fit all: A toolkit and taxonomy of ai explainability techniques," 2019, *arXiv:1909.03012*.

[48] A. B. Arrieta *et al.*, "Explainable artificial intelligence (XaI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Inf. Fusion*, vol. 58, pp. 82–115, 2020.

[49] R. Ying, D. Bourgeois, J. You, M. Zitnik, and J. Leskovec, "Gnnexplainer: Generating explanations for graph neural networks," *Adv. Neural Inf. Process. Syst.*, vol. 32, 2019, Art. no. 9240.

[50] M. T. Ribeiro, S. Singh, and C. Guestrin, "'why should i trust you?' explaining the predictions of any classifier," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Mining*, 2016, pp. 1135–1144.

[51] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in Neural Information Processing Systems 30*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. New York, NY, USA: Curran Associates, Inc., 2017, pp. 4765–4774. [Online]. Available: http://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf

[52] M. Lom, O. Pribyl, and M. Svitek, "Industry 4.0 as a part of smart cities," in *Proc. Smart Cities Symp. Prague*, 2016, pp. 1–6.

[53] S. Pellicer, G. Santa, A. L. Bleda, R. Maestre, A. J. Jara, and A. G. Skarmeta, "A global perspective of smart cities: A survey," in *Proc. 7th Int. Conf. Innov. Mobile Internet Serv. Ubiquitous Comput.*, 2013, pp. 439–444.

[54] Z. Allam and Z. A. Dhunny, "On Big Data, artificial intelligence and smart cities," *Cities*, vol. 89, pp. 80–91, 2019.

[55] D. Thakker, B. K. Mishra, A. Abdullatif, S. Mazumdar, and S. Simpson, "Explainable artificial intelligence for developing smart cities solutions," *Smart Cities*, vol. 3, no. 4, pp. 1353–1382, 2020.

[56] F. Shrouf, J. Ordieres, and G. Miragliotta, "Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage.*, 2014, pp. 697–701.

[57] S. Grabowska, "Smart factories in the age of Industry 4.0," in *Management Systems in Production Engineering*, vol. 28, no. 2, pp. 90–96, doi: 10.2478/mspe-2020-0014.

[58] J. Wan, J. Yang, Z. Wang, and Q. Hua, "Artificial intelligence for cloud-assisted smart factory," *IEEE Access*, vol. 6, pp. 55419–55430, 2018.

[59] M. Javaid and A. Haleem, "Industry 4.0 applications in medical field: A brief review," *Curr. Med. Res. Pract.*, vol. 9, no. 3, pp. 102–109, 2019.

[60] M. N. Chawla, "AI, IoT and wearable technology for smart healthcare—A review," *Int J. Green Energy*, vol. 7, no. 1, pp. 9–13, 2020.

[61] U. Pawar, D. O'Shea, S. Rea, and R. O'Reilly, "Explainable ai in healthcare," in *Proc. Int. Conf. Cyber Situational Awareness, Data Anal. Assessment*, 2020, pp. 1–2.

[62] C. Krupitzer *et al.*, "A survey on human machine interaction in Industry 4.0," 2020, *arXiv:2002.01025*.

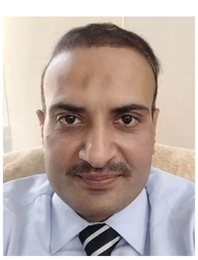
[63] C. Meske and E. Bunde, "Transparency and trust in human-AI-interaction: The role of model-agnostic explanations in computer vision-based decision support," in *Proc. Int. Conf. Hum.-Comput. Interaction*, 2020, pp. 54–69.

[64] Z. Li, Y. Wang, and K.-S. Wang, "Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario," *Adv. Manuf.*, vol. 5, no. 4, pp. 377–387, 2017.

[65] M. Paolanti, L. Romeo, A. Felicetti, A. Mancini, E. Frontoni, and J. Loncarski, "Machine learning approach for predictive maintenance in Industry 4.0," in *Proc. 14th IEEE/ASME Int. Conf. Mechatronic Embedded Syst. Appl.*, 2018, pp. 1–6.

[66] B. Hrnjica and S. Softic, "Explainable AI in manufacturing: A predictive maintenance case study," in *Proc. IFIP Int. Conf. Adv. Prod. Manage. Syst.*, 2020, pp. 66–73.

[67] P. Zajec, J. M. Rožanec, I. Novalija, B. Fortuna, D. Mladenić, and K. Kenda, “Towards active learning based smart assistant for manufacturing,” *Adv. Prod. Manage. Syst. Artifi. Intell. Sustain. Resilient Prod. Syst.*, 2021, doi: 10.1007/978-3-030-85910-7.
[68] M. L. Nunes, A. Pereira, and A. C. Alves, “Smart products development approaches for Industry 4.0,” *Procedia Manuf.*, vol. 13, pp. 1215–1222, 2017.
[69] A. G. Frank, L. S. Dalenogare, and N. F. Ayala, “Industry 4.0 technologies: Implementation patterns in manufacturing companies,” *Int. J. Prod. Econ.*, vol. 210, pp. 15–26, 2019.
[70] T. Tomiyama, E. Lutters, R. Stark, and M. Abramovici, “Development capabilities for smart products,” *CIRP Ann.*, vol. 68, no. 2, pp. 727–750, 2019.
[71] I. Malý, D. Sedláček, and P. Leitao, “Augmented reality experiments with industrial robot in Industry 4.0 environment,” in *Proc. IEEE 14th Int. Conf. Ind. Informat.*, 2016, pp. 176–181.
[72] B. C. Ervural and B. Ervural, “Overview of cyber security in the Industry 4.0 era,” in *Industry 4.0: Managing the Digital Transformation*. Berlin, Germany: Springer, 2018, pp. 267–284.
[73] E. Darraj, C. Sample, and C. Justice, “Artificial intelligence cybersecurity framework: Preparing for the here and now with AI,” in *Proc. 18th Eur. Conf. Cyber Warfare Security. Acad. Conf. Publishing Limited*, 2019, pp. 132–141.
[74] J.-H. Li, “Cyber security meets artificial intelligence: A survey,” *Front. Inf. Technol. Electron. Eng.*, vol. 19, no. 12, pp. 1462–1474, 2018.
[75] M.-C. Chang *et al.*, “AI city challenge 2019-city-scale video analytics for smart transportation,” in *Proc. CVPR Workshops*, 2019, pp. 99–108.
[76] F. Zantalis, G. Koulouras, S. Karabetsos, and D. Kandris, “A review of machine learning and IoT in smart transportation,” *Future Internet*, vol. 11, no. 4, p. 94, 2019, doi: 10.3390/fi11040094.
[77] R. Gupta, S. Tanwar, N. Kumar, and S. Tyagi, “Blockchain-based security attack resilience schemes for autonomous vehicles in Industry 4.0: A systematic review,” *Comput. Elect. Eng.*, vol. 86, 2020, Art. no. 106717.
[78] J. Hill, W. R. Ford, and I. G. Farreras, “Real conversations with artificial intelligence: A comparison between human-human online conversations and human-chatbot conversations,” *Comput. Hum. Behav.*, vol. 49, pp. 245–250, 2015.
[79] H. Qin *et al.*, “Autonomous exploration and mapping system using heterogeneous UAVs and UGVs in GPS-denied environments,” *IEEE Trans. Veh. Technol.*, vol. 68, no. 2, pp. 1339–1350, Feb. 2019.
[80] C. Benevolo, R. P. Dameri, and B. D’auria, “Smart mobility in smart city,” in *Empowering Organizations*. Berlin, Germany: Springer, 2016, pp. 13–28.
[81] P. Zheng *et al.*, “Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives,” *Front. Mech. Eng.*, vol. 13, no. 2, pp. 137–150, 2018.
[82] V. Roblek, M. Meško, and A. Krapež, “A complex view of Industry 4.0,” *Sage Open*, vol. 6, no. 2, 2016.
[83] W. Xu, “Toward human-centered AI: A perspective from human-computer interaction,” *Interactions*, vol. 26, no. 4, pp. 42–46, 2019.
[84] I. Ahmed, M. Ahmad, G. Jeon, and F. Piccialli, “A framework for pandemic prediction using big data analytics,” *Big Data Res.*, vol. 25, 2021, Art. no. 100190.



Imran Ahmed (Senior Member, IEEE) received the B.Sc. degree in computer science and mathematics from Edwardes College Peshawar, Peshawar, Pakistan, in 1999, the M.Sc. degree in computer science from the University of Peshawar, Peshawar, in 2001, the MS-IT degree from the Institute of Management Sciences, Hayatabad, Peshawar, with major research in computer vision, and the Ph.D. degree in computer science from the University of Southampton, Southampton, U.K., in 2007 and 2014.

He is currently an Associate Professor with the Institute of Management Sciences, Hayatabad, Peshawar. He has attended several national and international conferences in these areas. His research interests include deep learning, machine learning, data science, computer vision, feature extraction, digital image and signal processing, medical image processing, biometrics, pattern recognition, and data mining.

Dr. Ahmed has been a reviewer in journals such as IEEE INDUSTRIAL ELECTRONICS, IEEE ACCESS, *Journal of Ambient Intelligence*, *Elsevier*, etc.

Gwanggil Jeon (Senior Member, IEEE) received the B.S., M.S., and Ph.D. (*summa cum laude*) degrees from the Department of Electronics and Computer Engineering, Hanyang University, Seoul, South Korea, in 2003, 2005, and 2008, respectively.

From September 2009 to August 2011, he was with the School of Information Technology and Engineering, University of Ottawa, Ottawa, ON, Canada, as a Postdoctoral Fellow. From September 2011 to February 2012, he was with the Graduate School of Science and Technology, Niigata University, Niigata, Japan, as an Assistant Professor. From December 2014 to February 2015 and June 2015 to July 2015, he was a Visiting Scholar with Centre de Mathématiques et Leurs Applications (CMLA), École Normale Supérieure Paris-Saclay (ENS-Cachan), Cachan, France. From 2019 to 2020, he was a Prestigious Visiting Professor with Dipartimento di Informatica, Universitá degli Studi di Milano Statale, Milan, Italy. He is currently a Professor with Xidian University, Xi’an, China, and with Incheon National University, Incheon, South Korea. He was a Visiting Professor with Sichuan University, Chengdu, China, Universitat Pompeu Fabra, Barcelona, Spain, Xinjiang University, Ürümqi, China, the King Mongkut’s Institute of Technology Ladkrabang, Bangkok, Thailand, and the University of Burgundy, Dijon, France.

Dr. Jeon is currently an Associate Editor of Sustainable Cities and Society, IEEE ACCESS, *Real-Time Image Processing*, *Journal of System Architecture*, and *MDPI Remote Sensing*. He was a recipient of the IEEE Chester Sall Award in 2007, the ETRI Journal Paper Award in 2008, and Industry-Academic Merit Award by Ministry of SMEs, and Startups of Korea Minister in 2020.

Francesco Piccialli (Member, IEEE) received the Laurea degree (B.Sc.+M.Sc.) in computer science and the Ph.D. degree in computational and computer sciences from the University of Naples Federico II (UNINA), Naples, Italy, in 2012 and 2016.

He is currently an Assistant Professor (tenure track) of Computer Science with the Department of Mathematics and Applications “R. Caccioppoli” (DMA), UNINA. In 2018, he took the Italian Scientific Habilitation for Associate Professorship. He has been involved in research and development projects in the research areas of artificial intelligence, data science, and Internet of Things.

Dr. Piccialli served editorial boards of numerous top-ranking and international journals. He is the Founder and Scientific Director of the M.O.D.A.L. research group that is engaged in cutting-edge on novel methodologies, applications and services in data science and machine learning fields, and their emerging application domains.