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Editorial

Big Data and AI for Process Innovation in the Industry 4.0 Era

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1. Introduction

The fourth industrial revolution or what can be referred to as Industry 4.0 encompasses an accumulation of technological advances in fields such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data, and Process Mining. With the introduction of distributed, collaborative, and automated processes, production and logistics systems have been revolutionized. Big Data Analytics (BDA), for example, is a process of examining immense and diverse data sets in order to discover new knowledge such as hidden patterns and correlations, market insights, and customer preferences. This Special Issue presents a comprehensive review of the exemplary studies and research related to Industry 4.0, IoT, Process Mining, and BDA. In the following sections, we provide a brief overview of each of these fields and showcase their promising applications. Lastly, we discuss the challenges and directions of future research in the context of Industry 4.0.

2. Industry 4.0

Industry 4.0 has revolutionized process innovation and facilitated and encouraged many new possibilities thereof. The objective of Industry 4.0 is the radical enhancement of productivity, the goal of which is ultimately dependent on enterprise processes. With regard to the problems inherent in process innovation, Big Data and AI have been considered key solutions. BDA is a process of examining data to discover knowledge such as unknown patterns and correlations, market insights, and customer preferences, all of which can be useful in making various business decisions. Significant advances in deep learning, machine learning, and data mining have improved to the point where they can be applied to the analysis of Big Data in any kind of industry. In fact, Big Data, with its sophisticated algorithms and advanced computing power, is also recognized as a fundamental technology for affecting advances in AI. In this sense, Big Data and AI are becoming core assets of Industry 4.0 and process innovation.

3. Internet of Things (IoT)

IoT represents a system or network of physical objects or “things” that can be used to deliver and exchange information and data with other systems over the internet. The term was first introduced by Kevin Ashton in 1991 in an attempt to make a system whereby the physical world and the Internet are interconnected through ubiquitous sensors, instruments, and other devices. The rapid development and progress of IoT have enabled businesses and industries to utilize communication devices such as sensors, RFID, smart grid applications, actuators, and mobile devices. For instance, in the paper “CNN-Based Defect Inspection for Injection Molding Using Edge Computing and Industrial IoT Systems” by Ha and Jeong [1], a defect-inspection system for an injection molding process application using edge intelligence was developed. Its use decisively overcame the data shortage and imbalance issues of small- and medium-sized enterprises (SMEs) through data augmentation. It

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yielded 90% accuracy, which proves that this system can be used in real-world applications. In another study, "Study on Reverse Logistics Focused on Developing the Collection Signal Algorithm Based on the Sensor Data and the Concept of Industry 4.0" by Sung, Kim, and Kim [2], sensors were also utilized to handle the proper disposal of small- and medium-volume electronic waste (e-waste). Sensor data and IoT were utilized by means of a collection of signal algorithms to enable proper collection of e-wastes and to promote more and better recycling.

Another application of IoT can be seen in the paper "Passive Radio-Frequency Identification Tag-Based Indoor Localization in Multi-Stacking Racks for Warehousing" by Park, Kim, and Lee [3]. In this study, passive radio-frequency technology (RFID) was applied for indoor inventory localization. In contrast with active RFID, passive RFID is relatively more cost-efficient for the same results. In a different application, the study "Smart Grid for Industry Using Multi-Agent Reinforcement Learning" by Roesch, Linder, Zimmermann, Rudolf, Hohmann, and Reinhart [4] used smart grids in an effort to reduce electricity consumption for industrial sites. This paper presented a multi-agent reinforcement learning (MARL) approach for energy-oriented production control. Given the high cost-reduction potential of this combination approach, all available power supply options were considered.

Lastly, the paper "Reconfiguration Decision-Making of IoT based Reconfigurable Manufacturing Systems" by Han, Chang, Hong, and Park [5] discussed the use of IoT sensors in gathering information hidden inside systems. This paper focused on the application of reconfigurable manufacturing systems (RMS) and the use of a decision-making algorithm for detection of reconfiguration situations. The algorithm was tested and verified in a simulation experiment, which proved the improvement of the RMS system applied.

4. Process Mining (Process Innovation)

Process analytics is the methodology used to understand, manage, and improve business processes by specifying each of the given factors and explaining their interrelationships. Based on an analysis of the situation of a particular field, process analytics can determine proper actions that analysts and managers can implement into their businesses. Additionally, process mining is a group of techniques related to process analytics that can be employed to support process analytics based on event logs. Some process mining techniques include process discovery, conformance checking, and process enhancement. The objective of process mining is to transform event logs or event data into insights and actions to support the analysis of business processes.

On this point, the paper "Quality-Aware Resource Model Discovery" by Cho, Park, Song, Lee, and Kum [6] developed a new method for the derivation of quality-aware resource models by collecting event logs such as the given company's activities, originators, timestamps, and product quality as data sets. This approach is effective for understanding the relationship between resource paths and resource quality. In the paper "Mining Shift Work Operation from Event Logs" by Utama, Sutrisnowati, Kamal, and Bae [7], a practical approach that combines process mining with resource availability in shift work operations is presented. The study utilized a self-organizing map and k-means clustering to incorporate the shift-work information that can be inputted to the simulation model. The simulation showed that the incorporation of shift-work operations can yield more accurate results. The paper "Towards a Domain-Specific Modeling Language for Extracting Event Logs from ERP Systems" by Pajić Simović, Barbarogić, Pantelić, and Krstović [8] presented a domain-specific modeling language to facilitate extraction of significant data from transactional databases by domain experts. Its applicability was demonstrated through an empirical-data-based case study, which showed that the developed language provides information sufficient for the collection and transformation of data from ERP databases.

Finally, the paper "PRANAS: A Process Analytics System Based on Process Warehouse and Cube for Supply Chain Management" by Kim, Obregon, and Jung [9] combined process-oriented and data-oriented analyses. This was accomplished using their own developed system called PRANAS, which applies process warehouse and process cube methods to assess supply chain management application performance.

5. Big Data Analytics (Artificial Intelligence)

Big Data Analytics (BDA) is one of the main foundations of Industry 4.0. BDA can examine immense amounts of information to uncover correlations and hidden patterns in data sets. Certainly then, it is a tool that can enhance business performance and increase competitive advantage [10]. There are different approaches to and applications for BDA. In the study "Dual-Kernel-Based Aggregated Residual Network for Surface Defect Inspection in Injection Molding Processes" by Lee and Rui [11], convolutional neural networks (CNNs) were used to classify and detect product defects in processes with short cycle times. Dual-kernel-based aggregated residual networks were proposed for a visual inspection system's automatic detection of injection mold process defects. Another neural-network-based approach that was presented in the "Comparative Study on Exponentially Weighted Moving Average Approaches for the Self-Starting Forecasting" by Yu, Kim, Bai, and Han [12] focused on applications of exponentially weighted moving average (EWMA) models using time-series information as a forecasting process. After conducting simulation scenarios, they recommended using a two-stage EWMA model as a base model for conducting a self-stating forecasting process for complex time series. Another study, "Implementation of a Blood Cold Chain System Using Blockchain Technology" by Kim, Kim, and Kim [13] utilized private blockchain techniques to increase information visibility in blood management information systems. Their proposed system is based on Hyperledger fabric networks to improve supply chain processes and traceability. Significantly, it could help patients in exigent circumstances by reducing blood supply times. Lastly, in the study "A Data-Driven Analysis on the Impact of High-Speed Rails on Land Prices in Taiwan" by Low and Lee [14], the correlation between the presence of high-speed rail (HSR) networks and other important dimensions of land-price appraisal was analyzed.

6. Conclusions

Further to and based on the studies already conducted and reviewed in this editorial, efforts continue to be made in developing new algorithms, systems, and technologies that can enable autonomous decision-making processes and real-time evaluations. When looking at the studies related to IoT, Process Mining, and BDA, there are still relatively few cases of successful application of these technologies in the various fields of Industry 4.0. Although this Special Issue is now closed, more in-depth exploration of Big Data and AI for their potential applications in process innovation is expected.

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