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Forecasting analytics for industry 4.0

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Abstract: This research through a systematic review highlights studies that have delved into analytics for Industry 4.0 with the aim of discussing and reflecting on the manner in which applications of Artificial Intelligence such as Machine Learning and Deep Learning have helped in forecasting and facilitated informed decision-making.
Keywords: *Analytics, Forecasting, Industry 4.0, Machine learning, Prediction.*

1. Introduction

The ecosystem of advanced analytics tools and big data technologies has evolved rapidly over the past years, offering new possibilities for data-driven solutions and digital transformations. In the contemporary world, the industry 4.0 environment connects machines as a collaborative community. Lee, Kao, & Yang [9] reiterate that such evolution requires the utilization of advanced prediction tools that can be able to process data systematically into information to explain uncertainties in such a way that such information can help enterprises and forecasters to make informed decisions. In the context of forecasting analytics for Industry 4.0, subsets of artificial intelligence (AI) such as machine learning (ML) algorithms and deep learning (DL) have proved effective in improving forecasting and predictive analytics for many firms operating in Industry 4.0 environment. Noteworthy, many of these firms are in the manufacturing and logistics segments.

The purpose of this research is to review and document studies that have delved into analytics for Industry 4.0 with the aim of shedding light on the manner in which applications of AI such as ML and DL have helped in forecasting and facilitated informed decision-making.

2. Forecasting Analytics for Industry 4.0

The topic of forecasting analytics in Industry 4.0 has receive extensive coverage in both empirical and theoretical studies. Bajic, Cosic, Lazarevic, Sremcev, & Rikalovic [2] explored machine learning (ML) techniques in Industry 4.0 with specific emphasis on applications and challenges to smart manufacturing. According to the researchers, Industry 4.0 is creating new opportunities through changing traditional manufacturing into smart manufacturing, with machines learning to understand these processes, interacting with environment, and adapting their behavior intelligently. Consistent with the assertions by Cioffi, Travaglioni, Piscitelli, Petrillo, & Felice [6], Bajic et al. [2] underscore the importance of using advanced methods, algorithms, technologies, and software in order to extract and collect data from the manufacturing environment.

Similar to the study by Bajic et al. [2], Cioffi et al. [6] also endeavored to investigate machine learning and artificial intelligence applications in smart production, albeit with specific emphasis on trends, progress, and development. To accomplish their goals, the researchers utilized a systematic literature review approach, searching the SCOPUS and Web of Science databases, and then utilizing UCINET software to complete the analysis. The reviewers settled on a final sample of 82 articles for review. A recurrent theme in the articles reviewed was that with the introduction of Industry 4.0, machine learning and artificial intelligence were major drivers in forecasting analytics of the smart factory revolution. The study by Cioffi et al. [6] also established that smart production systems need

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innovative solutions in order to increase the sustainability and quality while reducing costs of the manufacturing activities.

The studies by Bajic et al. [2] and Cioffi et al. [6] also have some other points of convergence. For example, both investigations revealed that AI-driven technologies, supported by I4.0 Key Enabling Technologies such as Internet of Things, big data, cloud computing, advanced embedded systems, virtual and augmented reality, and cognitive systems are ready to produce new industrial paradigms in Industry 4.0. Bajic et al. [2] in their analysis acknowledge that ML is becoming the most important technique used for predicting and classifying the difficulty of solving problems inside of the production systems. The researchers further contend that ML utilizes increased computing power coupled with various software for gaining the meaningful knowledge and information from the big data collected from the production environment.

The utility of ML for forecasting analytics for Industry 4.0 as identified by Bajic et al. [2] and Cioffi et al. [6] stems from its ability to learn from the data collected through getting the computational/artificial intelligence. Classified by the available feedback, the most important techniques used for learning in the industry 4.0 are reinforcement, supervised, and unsupervised techniques. Cadavid, Lamouri, Grabot, Pellerin, & Fortin [5] in a similar light also state that with the advent of industry 4.0, high computing power, copious availability of data, and large storage capacity, machine learning (ML) approaches have emerged as an appealing solution to enhancing predictive analytics and tackling manufacturing challenges.

The rapid evolution of technologies interconnected with internet of things and ICT enabled the growth of manufacturing that led to Industry 4.0. Bajic et al. [2] contend that the implementation of cyber-physical systems (CPS) combined with internet of things can provide flexible, intelligent systems that are capable of self-learning that represents the core of Industry 4.0. Nevertheless, in order to achieve flexible and intelligent systems, there is a requirement of big data. Cadavid et al. [5] concur with Bajic et al. [2] by asserting that in big data's knowledge discovery in databases (KDD), machine learning along with data mining, pattern recognition, statistic and other methods play an important role. As a major part of the intelligent system in Industry 4.0, ML helps in the generation of new information/knowledge that supports the process of making accurate predictions or decision making in the manufacturing and other environments. This is because of its immense ability at pattern recognition among data sets that describe the structure and relationships among those sets.

Alcácer & Cruz-Machado [1], akin to Cioffi et al. [6] performed a literature review with specific emphasis on forecasting analytics of technologies for manufacturing systems within the context of Industry 4.0. As the researchers rightly mention, Industry 4.0 leads to the digitization era. The researchers found out that most of the reviewed literature identified nine pillars or building blocks of the industry 4.0 framework. These pillars, in addition to those identified by Bajic et al. [2], include the industrial internet of things, cloud computing, big data, simulation, augmented reality, additive manufacturing, horizontal and vertical systems integration, autonomous robots, and cyber security. For Industry 4.0 success, Alcácer & Cruz-Machado [1] acknowledge that data security is necessary.

Based on real-world cases of predictive quality management and an extensive review of literature, Lee, Lee, & Kim [10] sought to present new, novel ideas for predictive quality management grounded on new technologies. The real-world cases used in this investigation included Rolls Royce, Hyundai Motors, BOSCH, Clova, and John Deere. The researchers contend that the industry 4.0 era necessitates new quality management systems because of the advent of advanced digital technologies and the ever-increasing complexity of the global business environment, an opinion also shared by Lasi et al. [8]. After conducting their analysis, results by Lee et al. [10] indicated that advanced technology facilitated predictive maintenance in the advanced industries studied. They also established that this predictive maintenance could find direct application to various industries through capitalizing on big data analytics, AI, smart sensors, and platform construction. The investigation by Lee et al. [10] further disclosed that such predictive management systems could become living ecosystems with the potential of performing cause-effect analysis, big data analytics and monitoring, and fostering effective decision-making in real world.

Nagy, Oláh, Erdei, Máté, & Popp [11] from a different dimension sought to investigate the predictive analytics of Industry 4.0 and the internet of things on the business strategy of the value chain in Hungary. The researchers affirm that in the era of digitalization, companies "are increasingly investing in tools and solutions that allow their processes, machines, employees, and even the products themselves, to be integrated into a single integrated network for data collection, data analysis, the evaluation of company development, and performance improvement" (p. 3491). Nagy et al. [11] utilized Porter's value chain model in studying the effect on Industry 4.0 on the company. In their investigation, they applied a dual methodology that involved sending online questionnaires to logistical and manufacturing services as well as conducting expert interviews with manufacturing firms to ascertain the manner in which these firms are able to forecast analytics for Industry 4.0.

During their research, Nagy et al. [11] found out that the spread of real-time data across firms, given the availability of appropriate methods and tools, could have a significant effect on the entire firm including the ability to make accurate forecasts and decisions. Just like in the study by Cioffi et al. [6], Nagy et al. [11] established that companies using cyber physical system (CPS), cyber physical production systems (CPPS), and dig data technologies had a higher level of logistic service, improved coordination between various logistics functions, more efficient processes with their partners, higher competitiveness, and higher financial and market performance. Moreover, companies in Hungary that utilized ML techniques benefited from uncovering intricate production patterns and timely decision support in areas such as process optimization, predictive maintenance; task scheduling, supply chain, sustainability, and quality improvement [11].

Taking a different approach, Bonnard, Vieira, Arantes, Lorbieski, & Nunes [4] concentrated their inquiry on small and medium sized enterprises (SMEs). The aim of their study was to present the methodology, development, and implementation of a new cloud-computing platform for collecting, storing, and processing data from industrial SME companies in Brazil. The objective was to implement and test the platform that employs more and more intelligent and connected devices to producing thousands of data that when computed achieve high value addition. In line with their study, Bonnard et al. [4] presented the architecture that they developed to collect data and store this data in a Big Data solution, after which they would process it with advanced AI algorithms and optimization techniques.

In the architecture developed by Bonnard et al. [4], communication between the different components occurred via Application Programming Interface (API) and Representational State Transfer (REST). The system has a frontend dashboard component representing a web interface or mobile application via which the user could interact with the environment. According to Bonnard et al. [4], frontend requested data from the backend that represented the intermediate component. Analytics in this model represented the component that had the intelligence demanded, an approach also utilized and reinforced by Tao, Qi, Liu, & Kusiak [15]. Analytics consumed data from the big data structure and backend, after which the researchers implemented the analytics using various AI techniques including ML, genetic algorithm, neural networks, and data mining. Following the implementation, the information or forecast provided by the data analysis facilitated decision-making support from which the SMEs could develop action plans.

In the study by Tao et al. [15], the scholars discussed the role played by big data in Industry 4.0 environment to support smart manufacturing. The researchers aver that advance in big data, the internet of things, internet technology, cloud computing, and artificial intelligence have had a profound effect on manufacturing, with the volume of data in manufacturing growing exponentially. Consistent with the assertions by Bonnard et al. [4], Tao et al. [15] acknowledge that big data empowers firms to adopt data-driven strategies that enhance their predictive capabilities and make them more competitive. The researchers from this inquiry concluded that big data analytics, in conjunction with machine learning, equips manufacturing enterprises with a specific kind of case-based reasoning capacity that can help in preventing recurrence of similar problems in the future [15].

Besides machine learning, other techniques identified by Tao et al. [15] and Bonnard et al. [4] that can enhance the effectiveness of data analytics in Industry 4.0 environment include large scale computing as well as the use of other forecasting models. Schuh, Potente, Wesch-Potente, Weber, & Prote [12] echo similar sentiments, adding that advanced data mining techniques such as clustering, regression, classification, prediction, association rules, and deviation analysis can also find direct application in enhancing the effectiveness of data analytics in Industry 4.0. Through these data processing efforts, firms and forecasters can be able to derive understandable knowledge from a large quantity of ambiguous and dynamic raw date. In the data-driven smart manufacturing framework developed by Tao et al. [15], the researchers incorporated four modules, which were the manufacturing module, the data driver module, the real-time monitor module, and the problem-processing module. In the problem-processing module, firms and forecasters can identify and predict emerging problems, diagnose root causes, and recommend possible solutions.

Kabugo, Jämsä-Jounela, Schiemann, & Binder [7] took a unique orientation through proposing a process data-analytics platform centered and built around the concept of Industry 4.0 for a waste-to-energy plant. The platform developed by these researchers utilized the state-of-the-art industrial internet of things platforms, machine learning (ML) algorithms, and big data software tools. Specifically, the platform emphasized the use of machine learning methods for process data analytics while simultaneously taking advantage of big data processing tools and exploiting the currently available industrial grade cloud computing platforms. The researchers demonstrated the industrial applicability of the platform through the development of soft sensors for utilization in a waste-to-energy (WTE) plant constrained to control gaseous and particulate emissions.

Using the case study approach, the work by Kabugo et al. [7] investigated data-driven soft sensors for predicting hot flue gas temperature and syngas heating value. Among the data-driven methods studies in this investigation, the neural network-based NARX model demonstrated superior performance in predicting both hot flue gas temperature and syngas heating value. The modeling results, as was similarly in a study by Shang, Yang, Huang, & Lyu [14] showed that in cases where limited process knowledge about the process phenomenon exists, data-driven soft sensors could be effective tools for predictive data analytics. In the investigation by Shang et al. [14], the researchers employed deep learning, a popular data-driven approach in the domain of machine learning (ML), to build soft sensors and applied the model to an industrial case to approximate the heavy diesel 95% cut point of a crude distillation unit (CDU).

The inquiry by Shang et al. [14], like that of Kabugo et al. [7] revealed that deep learning was an effective tool for forecasting analytics for industry 4.0. Nevertheless, Shang et al. [14] go a step further to explain the rationale for why deep learning, a popular data-driven approach in the domain of machine learning (ML), is an effective predictive analytic tool for Industry 4.0. First, the researchers attribute the effectiveness of deep learning to its complex multilayer structure, which enables the network to contain richer information and consequently yield improved representation ability. Second, established as latent variable models, deep neural networks have a higher capability of describing highly correlated process variables. Moreover, "the deep learning is semi-supervised so that all available process data can be utilized and the deep learning technique is particularly efficient dealing with massive data in practice" ([14], p. 231).

From a different dimension, Bezobrazov, Anfilets, Dolny, and Yakimovich [3] proposed a system for predictive analytics for Industry 4.0, although they based their system on artificial neural network that encompassed both deep and shallow neural networks. According to the researchers, the Industrial Predictive Analytics for Industry 4.0 is a system that can predict as well as prevent machine breakdowns and failures through analyzing time-series data such as vibration, temperature and pressure received from sensors inherently embedded in machines and equipment. The rationale provided by Bezobrazov et al. [3] for basing their system on artificial neural networks and artificial intelligence stemmed from their reasoning that these networks permit the analysis of huge data generated from the manufacturing process and they have the capability of predicting what will go wrong, and when.

Whereas many theoretical and empirical studies have focused on predictive analytics for industry 4.0 using algorithms such as machine learning (ML), deep learning, and data mining, it is worth highlighting a study by Shamim, Cang, Yu, & Li [13] provided some management approaches for Industry 4.0 with specific emphasis on the human resource perspective. A management focus is an important consideration because of the many challenges that may be inherent in the industry 4.0 environment. As Shamim et al. [13] vividly point out, "Industry 4.0 considers the digital enhancement and reengineering of products" (5309). Highly differentiated customized products coupled with well-coordinated combination of products and services further characterize it as well, presenting challenges that require continuous learning and innovation.

According to Lasi, Fettke, Kemper, Feld, & Hoffmann [8] success in Industry 4.0 depends upon the innovation capability of the industry. This innovation capability is either about CPS (i.e. computer networks, embedded actuators, or sensors), product differentiation, reengineering, or some supply chain issues. If enterprises need to be smart, they require an accommodative climate for learning, innovation, and intelligent employees, which necessitates suitable management practices. Industry 4.0 needs to develop vibrant capabilities to manage business models successfully, to develop product portfolio, to enhance value chain systems and processes, risk management, and cultural management because of globalization. In Industry 4.0 environment, it is evident that firm will face many technological, economic, and social challenges that require innovative workforce and dynamic capabilities. The recommendations offered by Shamim et al. [13] as well as by Lasi et al. [8] in order to ensure proper forecasting analytics for Industry 4.0 include having effective, visionary leaders, providing staff members with appropriate, ongoing training, using extensive recruitment and selection procedures to hire the right staff, and having a performance appraisal system focused on employee development.

3. Reflection, Conclusion and the Future

Overall, this extensive review has provided deep insights pertaining to forecasting analytics for Industry 4.0. From the analysis, it has become evident that the ecosystem of advanced analytics tools and big data technologies has evolved rapidly over the past years, offering new possibilities for data-driven solutions and digital transformations. Much of the literature supports the notion that subsets of AI such as ML and DL algorithms have great potential in improving forecasting analytics for Industry 4.0.

Moreover, advanced data mining techniques such as clustering, regression, classification, prediction, association rules, and deviation analysis can also find direct application in enhancing the effectiveness of data analytics in Industry 4.0. Through these data processing efforts, firms and forecasters can be able to derive understandable knowledge from a large quantity of ambiguous and dynamic raw date.

However as in any other study, ML and DL come with the usual caveat of being 'black-box' approaches and thus no elements of causality are established in such studies, and that makes many of the users in industry skeptic about the use and the origins of them. With that been said, the more than often success of such ML and DL approaches usually move the discussion of the respective adoption more pertinent that anything else. We leave this causality chase and quest for the future and focus now on the overwhelming successes we see more and more often in Industry 4.0.

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References

[1] Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: A literature review on technologies for manufacturing systems. Engineering Science and Technology, an International Journal, 22(3), 899-919.

[2] Bajic, B., Cosic, I., Lazarevic, M., Sremcev, N., & Rikalovic, A. (2018). Machine Learning Techniques for Smart Manufacturing: Applications and Challenges in Industry 4.0. 9th International Scientific and Expert Conference TEAM 2018, 29-38.

[3] Bezobrazov, S., Anfilets, S., Dolny, R., & Yakimovich, D. (2019). Predictive analytics for Industry 4.0. International Scientific Journal Industry 4.0., 6, 273-276.

[4] Bonnard, R., Vieira, K., Arantes, M. D., Lorbieski, R., & Nunes, M. (2019). A big data / analytics platform for Industry 4.0 implementation in SMEs. AutoManSec 4 CloudIoT, 1-9.

[5] Cadavid, J. P., Lamouri, S., Grabot, B., Pellerin, R., & Fortin, A. (2020). Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. Journal of Intelligent Manufacturing, 31, 1531-1558.

[6] Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & Felice, F. D. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends and directions. Sustainability, 12(2), 1-26.

[7] Kabugo, J. C., Jämsä-Jounela, S.-L., Schiemann, R., & Binder, C. (2020). Industry 4.0 based process data analytics platform: A waste-to-energy plant case study. International Journal of Electrical Power & Energy Systems, 115, 1-18.
[8] Lasi, H., Fettke, P., Kemper, H., Feld, D., & Hoffmann, D. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239-242.
[9] Lee, J., Kao, H., & Yang, S. (2014). Service innovation and smart analytics for Industry 4.0 and big data environment. Procedia CIRP, 16, 3-8.
[10] Lee, S., Lee, D., & Kim, Y. (2019). The quality management ecosystem for predictive maintenance in the industry 4.0 era. International Journal of Quality Innovation, 5(4), 1-11.
[11] Nagy, J., Oláh, J., Erdei, E., Máté, D., & Popp, J. (2018). The role and impact of Industry 4.0 and the Internet of Things on the business strategy of the value chain—The case of Hungary. Sustainability, 10, 3491.
[12] Schuh, G., Potente, T., Wesch-Potente, C., Weber, A. R., & Prote, J.-P. (2014). Collaboration mechanisms to increase productivity in the context of Industrie 4.0. Procedia CIRP, 19, 51-56.
[13] Shamim, S., Cang, S., Yu, H., & Li, Y. (2016). Management approaches for Industry 4.0: A human resource management perspective. IEEE Congress on Evolutionary Computation (CEC), 5309-5315.
[14] Shang, C., Yang, F., Huang, D., & Lyu, W. (2014). Data-driven soft sensor development based on deep learning technique. Journal of Process Control, 24, 223-233.
[15] Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, 157–169.