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# Smart Manufacturing with Analytics, Machine Learning and IoTs: A Perspective of Indian Home Goods Industry

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***Abstract*- With all the improvement of Internet of Things, and cloud computing solutions, the quantity of information from manufacturing methods is growing quickly. With substantial manufacturing details, achievements beyond expectations are produced to the product design, manufacturing, and keep procedure. Big data analytics were a primary know-how to encourage smart manufacturing methods. To be able to completely report BDA for intelligent production systems, this particular paper offers an extensive review of associated topics such as for instance the idea of big data, unit driven and information driven methodologies. The framework, key technologies, development, and programs of BDA for smart manufacturing methods are talked about. The opportunities and challenges for future investigation are highlighted. By means of this work, it's hoped to spark new concepts in the energy to notice the BDA for smart manufacturing methods.**

***Keywords:* manufacturing, machine learning, Indian home goods, analytics, IoT**

## 1. Introduction

With all the appearance of a new round of manufacturing revolution, info technology has hastened the integration of its with production methods, as well as the information run by businesses are becoming progressively wealthier, with features of volume, variety, and velocity [4]. For smart manufacturing, manufacturing major details not just promotes enterprises to effectively perceive the external and internal environment changes in the device but additionally facilitates systematic analysis as well as decision making to enhance the production process, minimize costs and enhance operational effectiveness. With substantial details, business modes are created from hope to empower the social growth as well as financial development. As a result, large industrial details are considered a mean of creation to traveling intelligent manufacturing [16].

With all the improvement of artificial intelligence, big data analytics happen to be significantly enhanced to successfully mine both organized as well as unstructured manufacturing details in smart production, that has turned into a new investigation hotspot [13]. Constant learning from big information of manufacturing system enables the device to be self-learning, self-regulation and self-optimization. together with the further advancement of BDA, the functioning of manufacturing methods is profoundly changed. To recognize the present state of re-search and give insights for future scientific studies, this particular paper systematically analyzes today's research initiatives, derive visible studies themes, and determine gaps in the present literature about big data analytics for smart production methods [9].

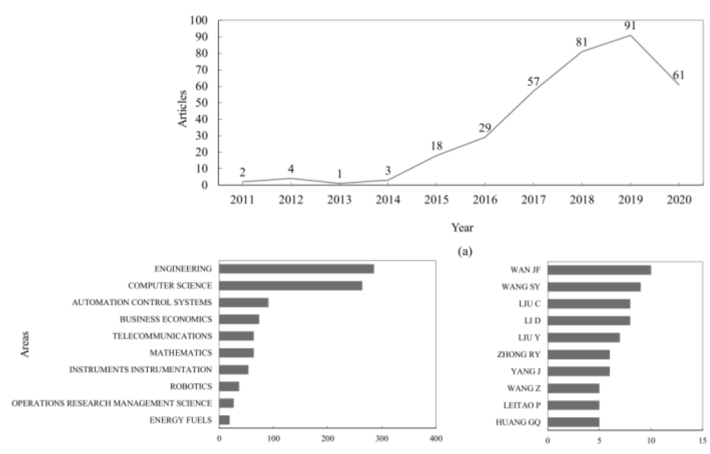


Fig 1: distributions of papers

A bibliometric evaluation was done with published data from 2011 to 2020 regarding smart production driven by great data gathered from the net of Science database, which often reveals a nearly constant rise in documents on this particular subject. Fig. one shows the number of articles that are published about intelligent manufacturing from 2011 to 2020. From 2011-2014, the quantities of articles are too small and have little change. But from 2014 to 2019, the amounts have been increased sharply and the ratio continues to cut up. Influenced by COVID 19, the amounts of pertinent articles posted in 2020 have reduced. Fig. one shows the best places related to smart manufacturing. As displayed in the chart, the best 5 aspects would be the Engineering, the computer Science, the Automation Control Systems, the company Economics and the Telecommunications [4]. The computer Science is considered the most related location for intelligent manufacturing. With all the technology developing quickly, the computer Science is going to be the crucial for breaking through the bottleneck of smart manufacturing [19]. Fig. one shows the prosperous scholars publishing in this specific place. Fig. one lists the best research or universities institutes publishing in this specific place [1]. These articles are sourced from the net of Science database with a focus on key ideas of big data and intelligent manufacturing. By examining these key technologies and associated academic motions, the way ahead is better and the subsequent new wave is coming soon enough [9].

## 2. Definitions and concepts

### 2.1. Concept of great data

With all the improvement of IoT, smart manufacturing has centered on the collection of BDA known as great information. Nevertheless, it's facing challenges that are great when making complete use of such information [2]. The constant production process, different sensing equipment and efficient and real-time information transmission help make the information have the standard qualities of "3V" of big data of volume, velocity and variety. Through additional evaluation of the information in manufacturing workshops, it's discovered to be recognized by multi source, imbalance, multi-noise, multi-dimension, and time series [22].

Multi-source: Together with the rise of the number and IoT technologies of receptors in workshops, the manufacturing information is saved and caught in multi sourced info methods with an alternative information building [13]. In order to incorporate multi source details in the production process, Zhu proposed a huge data analytics framework for sensible equipment quality monitoring, utilizing multi source info fusion technique to process picture data, 3d cloud data, and frequency signal data, get the monitor in addition to adaptively command of machining approach in time that is real under different working problems [3]. Sazu et al (2022) proposed a pixel amount fusion technique which fuses raw data from several sources into individual resolution information, and summarizes a few trends tending to broaden the use of multi source information fusion [27]. Tao assessed the dependency of information in merchandise lifecycle management under BDA atmosphere, and proposed a conceptual framework with increased overall flexibility, reliability, and much less computing time, that may cope with massive data and multi-source data. Zhang proposed a general architecture of multi source lifecycle BDA for item lifecycle, to make much better item lifecycle management as well as CP choices in manufacturing processes [19].

Multi-dimension: In production methods, the performance variables are affected by diverse elements, which results to a multidimension issue of control and prediction. The present techniques for multi-dimension problems could be classified into several types [22]. For instance, in semiconductor wafer production methods, the cycle time of wafer items is affected by over one 1000 components, like the processing time of every operation, the dimensions of waiting around queue for every machine, and the utilization of any machine [4]. In health problem monitoring of the devices, to completely examine the problems, state monitoring systems are utilized to obtain real time information from several sensors following the long time functioning. Aiming at the multi dimension function of manufacturing information, Liu proposed a novel incorporated system planning as well as management strategy dependent on smart application representatives as well as multi dimension production characteristics. Luo proposed a cloud production architecture to process multi dimension data, achieving on demand use, powerful collaboration, and blood flow of manufacturing information [16].

### 2.2. Concept of unit driven and information driven

Two primary paradigms for BDA: model driven, data-driven modes and. Model-Driven is the method to begin with a good idea of the way the actual physical system works. Model-driven approaches are effective because they depend on a full understanding of the device or process, and may benefit from scientifically developed relationships [5]. Models cannot accommodate infinite complexity and typically have to be simplified. They've trouble in producing a properly fitted unit accounting for noisy data in addition to non-included variables. For actual process scenarios, building up a complicated item combines the physical, data flow, electronic, mechanical, and any other right details of the intricate systems. Moreover, modeling will take time. It's inherently a trial-and-error strategy, rooted in the existing scientific method of theory based hypothesis formation and experiment based testing. Locating a good style and refining it unless it makes the desired results is normally a long process. The information driven approaches instruction with big data are called being great data driven.

## 3. Development and Framework

### 3.1. The framework of big data analytics for smart manufacturing systems

The main science paradigm of BDAIMS is information science, that had been highlighted in the guide entitled the quarter paradigm: information comprehensive medical find. In 2022, Jahan et al. pointed away from the viewpoint of medical research paradigm which information comprehensive science will be the other paradigm after experimental science, theoretical derivation and simulation [9]. The standard scientific research paradigms construct complicated mathematical versions to approximate actual methods via experiment, simulation and derivation, and analyzes as well as optimizes the device. In complicated large scaled dynamic methods, mathematical, well experimental, and simulation airers are difficult to be constructed. On the flip side, big data extracts understanding by mining the correlation between information, that can offer tougher insight, decision-making ability and analysis [11].

### 3.2. The development of big data analytics

The fundamental data analytics are enabled by the evolution of artificial intelligence, that may be split into 3 decades. 1) The very first generation of BDA The very first generation of BDA seeks to resolve complicated issues with straightforward algorithms. The symbolic labor was influenza epidemics detector from google [6]. This particular detector estimated the likelihood that a random doctor visit in a specific region was associated with an ILI signal that had been the same as the portion of ILI related doctor trips. In this particular detector, a linear regression design was created to model the connection between an ILI doctor visit and the log odds of an ILI related search query. With more and more Google search queries, the influenza like illness in a population was correctly monitored for every one of the 9 surveillance areas of the United States with no influenza transmission versions. Within the very first generation of BDA, information is viewed as the most crucial ingredient being a success.

## 4. Key technologies of big data analytics

### 4.1. Computation framework

With all the improvement of information sensing and Internet of Things technologies, the scale of information will continue to rise to achieve TB, PB, as well as higher degrees, that may not be performed by an individual computer. This puts forward higher demands for the computing power in addition to timeliness of the pc to process big information. Large information processing consists of the setup of the storage process, the division of computing jobs, the distribution of computing load, the information migration among computer systems, as well as the information protection whenever the personal computer or maybe community breaks [7]. The situation is a lot more complex. Distributed computing engineering, in terms that are simple, is the fact that several devices share computing tasks, and that is the primary option at current. Moreover, in certain manufacturing scenarios, on account of the steep real time details computation as well as analysis needs of a lot of equipment and processes in the bottom part of the creation process, the edge cloud computing architecture came into this world.

## 5. Application in manufacturing systems

Driven by smart sensing, Internet of Things, distributed storage computing, other technologies and machine learning, large data-driven smart manufacturing apps have started to come through. The uses in product design, scheduling and planning, quality optimization, maintenance and equipment operation were performed to substantialize the smart production devices [8].

### 5.1. Big data driven product design

Design plays a crucial role of manufacturing process, which decides the majority of a product 's performance and performance. With all the improvement of big data engineering, product design is shifting towards data driven look from subjective conceptual style. Large data driven product design analyzes the market demand through users' evaluation. Next, it generates the style scheme through the sale, purchaser, manufacturing information, and improves the decision-making power based on history learning. Finally achieves the closed loop optimization of self-monitoring, self-analyzing, self-learning and self-adaptation. Intelligent design is usually split into 2 elements based on the layout goals, one is product look for quality improvement, and the other is humanized condition style centered on client tastes. In the area of product design, a new digitized as well as parameterized perspective are formed in the era of big data. BDA offers a mechanism of good look with sleek design procedures, promoted merchandise innovations, and developed customized items by researching as well as understanding consumer requires, behaviors, and personal preferences [12].

Ireland brought Internet user evaluation into product design to attain a quantitative evaluation of merchandise capabilities and provided assistance for design choices. Xu proposed a framework of data driven product design for capturing item graphic aesthetics UX to successfully determine the helpful design ideas from customer personal preferences to customer reaction. Promotion techniques have been created to suit for corresponding sections of various clients. Li created a framework of intelligent item [15]. In this particular framework, pairwise relative algorithm was used to cluster specialized attributes into modules assembled into sensible items. Wireless sensor system was created to monitor sensible device, and K means algorithm was adopted to contend with checking information. Triangular fuzzy numbers were utilized to assess the maturity of the monitoring functionality. Lastly, the style of command functionality was motivated to make the perfect approach by Q-learning algorithm to notice the closed loop design [14].

### 5.2. Big data driven preparation and scheduling

Production preparation as well as scheduling is among the core problems of enterprise operation and control. In the perfect scenario, a feasible routine could effectively allocate production materials while coping with the effect of different on-site uncertainties [17]. Nevertheless, standard store floor scheduling strategies primarily focus on the workshop performance as well as resource utilization in static atmosphere, which might lead to infeasibility or deterioration of static agenda. Big data analytics present a series of good tools and methods for the production preparation as well as scheduling in environment that is dynamic. BDA is able to enhance the model of pattern in the planning as well as scheduling. A great amount of real-time information and historical data of the production process must be collected via different enterprise info systems, embedded intelligent machines and sensors, like the processing time of employment, the established time of machines, as well as the transport time of substances [13]. Based upon the collected data, big data analytics are able to offer extensive info help for scheduling decisions. For instance, prior to making manufacturing schedules, the distribution info of different unsure elements could be correctly estimated by statistical analysis methods. And then, strong optimization as well as smart optimization algorithms are utilized to formulate strong production plans as well as schedules under uncertain atmosphere [16].

### 5.3. Big data driven quality management

Large data driven product quality management realizes optimization and product traceability based on merchandise manufacturing process data as well as quality inspection data. The primary factors impacting product quality many, like raw material general performance parameters, equipment status parameters, procedure details, and workshop green details may be diagnosed by correlation evaluation [18]. Meanwhile, a mapping type between quality influencing factors as well as quality performance could be established to successfully predict product quality. Intelligent optimization algorithms are more utilized to adaptively correct management parameters which affect product quality in time that is real to achieve adaptive management as well as product quality [20].

To identify the primary key influencing parameters impacting the item quality from mass production parameters plays a crucial role as the input of the item quality management version. Sazu et al. (2022) screened out twelve highly correlated WAT aspects via specialist practical experience as unit feedback, and created an analysis technique dependent on modified Partial Least Square to filter main parameters [30]. This method needed the guru knowledge to select key details, that had been hard for quality analysts with no expertise to rapidly perfect this particular skill. Qin et al. old bench test information in the quality control of diesel engines to do correlation analysis on prospective details affecting energy consistency, as well as efficiently enhanced energy consistency [19]. These techniques analyze the correlation between the quality and candidate factors indicators to disclose the real cause of fluctuation.

Nevertheless, the correlation examined by present-day BDA differs from the genuine circumstance under several circumstances, since the observed correlation has not just accurate dependence but additionally noises attributable to transitive consequences of correlations [22]. As an outcome, the examined correlation could be heightened to mislead the primary key component identification. To really determine the real cause components, the causal inference embedded BDA might be further addressed to enhance the robustness as well as precision of BDA [23].

Controlling product quality is a crucial component of the development as well as production process. Jin et al. proposed a feedforward control technique depending on the linear model. The created engineering driven reconstruction technique of the linear regression tree more reduced the intricacy of the product by merging leaf nodes underneath the restrictions of balance accuracy demands. The usefulness of the proposed technique was verified to a multi stage wafer manufacturing process. Borja et al. pre-owned Reinforcement Learning analysis treatments to gain the necessary feedback controller for the ball screw feed drive to offer positioning accuracy. The suggested strategy done much better compared to PID controller in computational experiments.

Liu et al. regarded the function tensors extracted by CNN as interdependent characteristic sequences in the system of molten pool suggest recognition, and employed LSTM to mine the connection between the characteristic sequences to notice the real integration of unwanted capabilities extracted by CNN [21]. Liu et al. created a coarse grained regularization technique in view of the little sample issue experienced in the procedure for molten pool state recognition based on serious learning, since the qualities of the convolution procedure, which successfully avoided the product from overfitting. Chien et al. utilized a neural system design to fit the connection between WIP details, work size, the duration of the waiting queue prior to the bottleneck station, the length of the waiting queue on the task path as well as the building period to develop a routine management program. Chen et al. utilized the Gauss Newton regression design to determine the effect of the typical quantity of layers, production capacity, movement, other parameters and WIP on the building phase, and recognized the construction period influence on this particular foundation [24]. In the particular device production process, product quality typically has to be assessed by several quality indicators, each one of that is connected to one another calls for many tasks. The cooperative command with various adjustable controlled variables in the integration multi process with design, production as well as assembly remains an open concern.

### 5.4. Big data driven prognostics wellness management

Large data driven prognostics wellness management uncovers the time series switches in method fault qualities through real time monitoring of manufacturing process information, other time-series data and equipment performance parameters. The PHM information is completely examined to proactively determine possible anomalies in the device procedure in advance, identify the real cause of anomalies, and forecast the remaining lifestyle of a product. The analyzed PHM information includes acceleration signal, acoustic emission signals, temperature data, electrical data, optical signals, etcetera. In the PHM of a revolving machinery, Sinha et al. assessed the vibration signals gathered up by an acceleration sensor. For complex machinery, Lei et al. acquired as well as incorporated many acceleration sensors to keep track of the health problem of planetary gearboxes [26]. In the PHM of high speed moving machinery, Sazu et al. (2022) extended real time nearfield acoustic holography to reconstruct the instantaneous covering regular velocity of a vibrating framework from the time dependent strain measured in the near area, that offers a real-time and non-contact technique to calculate as well as imagine the transient vibration of the framework [27]. Acoustic emission is yet another signal popular in the PHM of slew bearing, cutting tool, and structure wellness monitoring apps. From the viewpoint of information, nearly all almost all of the present investigation with information inside a single media. The cross media BDA removing info from various medias is a crucial issue in the PHM.

Prior to the improvement of serious learning for BDA, the PHM techniques make choices based on pre extracted characteristics. There are many crucial and widely used features, which includes time-frequency domain-based element, spectral cliff-based characteristic, higher order statistical variable based feature, and random resonance based element [28]. The BDA merges 2 steps together, since serious learning methods can immediately extract features from raw time domain signals. Zheng et al. created a transfer locality preserving projection based smart fault identification technique, which embeds the information to some subspace via protecting a priori division system qualities and teaches a classifier to determine the state of goal computer by the historic information. In order to instruct the PHM design adaptively, Akter et al. (2022) created a novel learning fee scheduler dependent on reinforcement learning for convolutional neural network of fault classification, which could plan the mastering rate automatically and efficiently [25]. Lei's group designed a feature-based transfer neural network to discover transferable features from data collected in a lab to attain higher diagnosis accuracy for real case devices [29]. Present BDA offers an end-to-end architecture to instruct PHM versions with substantial details immediately. For manufacturing process, the functions, along with potential irregular signals, are changing with the powerful operation atmosphere. The BDA is able to discover knowledge regarding PHM with a self learning mechanism to conquer the unpredictable scenarios. Down the road, the end-to-end architecture might be enhanced with interpretable transformable quantizable learning solutions to substantialize a hybrid type [31].

## 6. Challenges for potential research

The BDA was viewed as probably the most essential technologies, thanks to the capacity of its to explore varied and large datasets to uncover hidden knowledge and patterns along with other helpful info. The discovered knowledge and patterns is able to help manufacturing methods to make more informed decisions, and then to accomplish the entire lifecycle optimization plus more sustainable production. The integration of existing understanding as well as the discovered knowledge and patterns out of big data will be a fascinating concern. From an additional perspective, the reuse learned knowledge and patterns out of grave details into BDA procedure will better the functionality of BDA strategies.

## 7. Conclusion

As increasing attention is provided to intelligent manufacturing methods, BDA is turning into a primary technology to give forecasting as well as decision making in manufacturing methods. BDA is a key upcoming perspective in each research and manufacturing community, as it offers extra value to different systems and products by implementing cutting edge technologies to conventional goods in manufacturing. Key concepts, key technologies, frameworks, apps are discussed in this specific paper. Open problems for future investigation are highlighted following a systematic review. We really hope this paper helps to advertise the technical and theoretical engineering and research application of large data driven intelligent manufacturing methods.

**References**

[1]. Gao RX, Wang L, Helu M, Teti R. Big data analytics for smart factories of the future. CIRP Ann 2020;69(2):668–92. https://doi.org/10.1016/j. cirp.2020.05.002.

[2]. Leng J, et al. A loosely-coupled deep reinforcement learning approach for order acceptance decision of mass-individualized printed circuit board manufacturing in industry 4.0. J Clean Prod 2021;280. https://doi.org/10.1016/j. jclepro.2020.124405.

[3]. Wang G, Gunasekaran A, Ngai EWT, Papadopoulos T. Big data analytics in logistics and supply chain management: certain investigations for research and applications. Int J Prod Econ 2016;176:98–110. https://doi.org/10.1016/j. ijpe.2016.03.014.

[4]. Jahan, S. A., & Sazu, M. H. (2022). Role of IoTs and Analytics in Efficient Sustainable Manufacturing of Consumer Electronics. International Journal of Computing Sciences Research, 6.

[5]. Zhang Z, et al. Pathologist-level interpretable whole-slide cancer diagnosis with deep learning. Nat Mach Intell 2019;1(May). https://doi.org/10.1038/s42256- 019-0052-1.

[6]. Parisi GI, Kemker R, Part JL, Kanan C, Wermter S. Continual lifelong learning with neural networks : a review. Neural Netw 2019;113:54–71. https://doi.org/ 10.1016/j.neunet.2019.01.012.

[7]. Kusiak A. Smart manufacturing must embrace big data. Nature 2017;544(7648). https://doi.org/10.1038/544023a.

[8]. Zhong RY, Newman ST, Huang GQ, Lan S. Big Data for supply chain management in the service and manufacturing sectors: challenges, opportunities, and future perspectives. Comput Ind Eng 2016;101. https://doi.org/10.1016/j.cie.2016.07.013.

[9]. Jahan, S. A., & Sazu, M. H. (2022). The Impact of Data Analytics on High Efficiency Supply Chain Management. CECCAR Business Review, 3(7), 62-72.

[10]. Dutton W, et al. Clouds, big data, and smart assets: ten tech-enabled business trends to watch. McKinsey Q 2010;(4).

[11]. Yager RR. A framework for multi-source data fusion. Inf Sci (Ny) 2004;163(1–3). https://doi.org/10.1016/j.ins.2003.03.018.

[12]. Zhu K, Li G, Zhang Y. Big data oriented smart tool condition monitoring system. IEEE Trans Ind Inform 2019;16(6):1. https://doi.org/10.1109/tii.2019.2957107.

[13]. Sazu, M. H., & Jahan, S. A. (2022). How Big Data Analytics Impacts the Retail Management on the European and American Markets. CECCAR Business Review, 3(6), 62-72.

[14]. Zhang J. Multi-source remote sensing data fusion: status and trends. Int J Image Data Fusion 2010;1(1). https://doi.org/10.1080/19479830903561035.

[15]. Tao F, Qi Q, Liu A, Kusiak A. Data-driven smart manufacturing. Int J Ind Manuf Syst Eng 2018;48:157–69. https://doi.org/10.1016/j.jmsy.2018.01.006.

[16]. Sazu, M. H., & Jahan, S. A. (2022). How Analytics Can Improve Logistics And Supply Chain In Multinational Companies: Perspectives From Europe And America. Business Excellence and Management, 12(3), 91-107.

[17]. Zhang Y, Ren S, Liu Y, Si S. A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. J Clean Prod 2017;142. https://doi.org/10.1016/j.jclepro.2016.07.123.

[18]. Chiara, D. E., Gonsalez, A. V., & Maria, A. C. (2022). Using Machine Learning and Analytics for Efficient Manufacturing Process. International Journal of Data Science and Advanced Analytics (ISSN 2563-4429), 4(4), 131-139.

[19]. Sazu, M. H., & Jahan, S. A. (2022). The impact of big data analytics on supply chain management practices in fast moving consumer goods industry: evidence from developing countries. International Journal of Business Reflections, 3(1).

[20]. Wang J, Yang J, Zhang J, Wang X, Zhang W (Chris). Big data driven cycle time parallel prediction for production planning in wafer manufacturing. Enterp Inf Syst 2018;12(6):714–32. https://doi.org/10.1080/17517575.2018.1450998.

[21]. Lei Y, Jia F, Lin J, Xing S, Ding SX. An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. IEEE Trans Ind Electron 2016;63(5). https://doi.org/10.1109/TIE.2016.2519325.

[22]. Sazu, M. H., & Jahan, S. A. (2022). High efficiency public transportation system: role of big data in making recommendations. Journal of process management and new technologies, 10(3-4), 9-21.

[23]. Liu C, Li Y, Shen W. Integrated manufacturing process planning and control based on intelligent agents and multi-dimension features. Int J Adv Manuf Technol 2014;75(9–12). https://doi.org/10.1007/s00170-014-6246-0.

[24]. Luo Y, Zhang L, Zhang K, Tao F. Research on the knowledge-based multi-dimensional information model of manufacturing capability in CMfg. Adv Mater Res 2012;472–475. https://doi.org/10.4028/www.scientific.net/amr.472-475.2592.

[25]. Akter, J. S., & Haque, S. M. (2022). Innovation Management: Is Big Data Necessarily Better Data. Management of Sustainable Development, 14(2), 27-33.

[26]. Xu C, Wang J, Zhang J. Forecasting the power consumption of a rotor spinning machine by using an adaptive squeeze and excitation convolutional neural network with imbalanced data. J Clean Prod 2020:122864. https://doi.org/10.1016/j.jclepro.2020.122864.

[27]. Sazu, M. H., & Jahan, S. A. (2022). Impact of big data analytics on distributed manufacturing: does big data help?. Journal of process management and new technologies, 10(1-2), 70-81.

[28]. O'Donovan P, Leahy K, Bruton K, O'Sullivan DTJ. Big data in manufacturing: a systematic mapping study. J Big Data 2015;2(1). https://doi.org/10.1186/ s40537-015-0028-x.

[29]. Lee DH, Yang JK, Lee CH, Kim KJ. A data-driven approach to selection of critical process steps in the semiconductor manufacturing process considering missing and imbalanced data. J Manuf Syst 2019;52. https://doi.org/10.1016/j.jmsy.2019.07.001.

[30]. Haque, S. M., & Akter, J. S. (2022). Big Data Analytics & Artificial Intelligence In Management Of Healthcare: Impacts & Current State. Management of Sustainable Development, 14(1), 36-42.

[31]. Zhao M, Kang M, Tang B, Pecht M. Deep residual networks with dynamically weighted wavelet coefficients for fault diagnosis of planetary gearboxes. IEEE Trans Ind Electron 2018;65(5). https://doi.org/10.1109/TIE.2017.2762639.