iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** VIII **Month of publication:** August 2022

DOI: https://doi.org/10.22214/ijraset.2022.46362

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VIII Aug 2022- Available at www.ijraset.com

Machine Learning Approaches, Technologies, Recent Applications, Advantages and Challenges on Manufacturing and Industry 4.0 applications

Muzakkiruddin Ahmed Mohammed
Electrical and Electronics Department, Lords Institute of Engineering and Technology

Abstract: This research is based at creatively employing machine learning to generate new ways, evaluate approaches, and communicate outcomes for difficulties encountered in the manufacturing business. Because manufacturers aim to increase profits with the least amount of capital expenditure, a model has been developed in which machine learning is integrated into manufacturing. It is critical to use all available means in order to meet the demand for high-quality products in an effective manner. Machine learning is one topic that has seen rapid advancement in terms of not just promising outcomes but also applicability. Machine learning is being widely explored by both academics and professionals as a potential solution to many of manufacturing's old and new obstacles. Unfortunately, the field is highly diverse and even perplexing, posing a difficulty and a barrier to widespread implementation. The linear regression algorithm was used to predict the outcome for the provided input, and gradient descent was used to optimise the output. It can assist the firm maximise output and profit by anticipating the outcome so that the company can take the necessary action or foresee the problem ahead of time. This study helps to structure this relatively intricate field by providing an overview of existing machine learning approaches. A particular emphasis is placed on the prospective benefit, as well as instances of successful implementations in a manufacturing context.
Keywords: Intelligent Manufacturing Systems; Smart Manufacturing; Artificial Intelligence; Machine Learning; Production; Manufacturing; Assembly; Potentials; Challenges; Applications; Industry 4.0

I. INTRODUCTION

Manufacturing is the large-scale manufacturing or assembling of components into completed goods. The digital revolution of manufacturing has the potential to boost domestic productivity and create new business models. Industry 4.0's innovative component is not only the digitization of products and their manufacture, but also the ability to integrate technological systems in real time [1]. It serves as one of the most significant industries in the world's economy, accounting for around 16% of global GDP in 2019 and generating a worldwide output of $13.9 trillion. The use of IoT technology has grown dramatically over the years, and the industrial sector has grown at a rapid pace in the previous decade. With the fast growth of Industry 4.0 and IoT technologies, more and more real-time on-site data from manufacturing lines is being captured. Data-driven methodologies may now be used to give solutions to different manufacturing process difficulties. The data collected in this manner can subsequently be examined and assessed using machine learning (ML) techniques, with the goal of improving quality, lead time, prices, or flexibility. As computational power and storage capacity increase, either on edge devices and maybe even cloud platforms, additional complex algorithms could be implemented [2]. Smart Manufacturing, a new area of manufacturing that has emerged as a result of Industry 4.0, provides opportunities for analysis in the domain. The digital twin concept is greatly facilitated by cloud computing, which makes use of internet connections to collect, analyse, and access information. Sophisticated technologies including automation and robotics, augmented and virtual environments, and additive manufacturing are being applied to help current generation production. Predictive maintenance, process optimization, task scheduling, quality improvement, supply chain, sustainability, and many other manufacturing and production applications are just a few of the areas where machine learning (ML), a branch of artificial intelligence (AI) technologies, has the possibilities to transform into primary driver in revealing fine-grained intricate production patterns in the smart manufacturing concept. It is a tech-driven strategy that makes use of the IoT and internet-connected technologies to manufacture products and keep track of processes. Its objective is to generate, optimise, and deploy massive amounts of data for automating industrial processes in order to improve efficiency, promote sustainability, supply chain management, and discover system obstacles before they emerge. Industries may get insights to enhance the efficiency of individual assets along with the entire manufacturing process by applying advanced analytics to industrial data, which is integrating artificial intelligence (AI) and machine learning (ML).

The objective of machine learning is to enable computers systems the ability to automatically get better at particular activities over time. The subject is strongly connected to statistical inference as well as pattern recognition. A significant portion of machine learning research has focused on classification, which is the process of creating a model from a set of instances that have already been successfully categorised in order to correctly classify new examples from the identical population. The research of computational learning and pattern identification theory gave rise to the data science discipline known as machine learning. It employs generalizable algorithms that excel at completing the desired objective. In today's industrial sectors, machine learning is often employed for a diverse range of tasks, including spam filters, fraud detection, medicine design, data prediction, speech recognition, illness diagnosis, etc. In order to increase productivity, this research focuses on creating a model of machine learning for the industrial sector. In order to predict the outcome for any input, a computer adapts from previously supplied sample data, known as training sets, and its effectiveness grows over time.

II. LITERATURE SURVEY OF MACHINE LEARNING APPROACHES

Artificial intelligence (AI) has several subfields, including machine learning (ML), which enables computers to learn without explicit programming [3]. Instead of using physical rules to represent the behaviour of a technological system, correlations are discovered using data, such as process and quality data. Unsupervised, supervised, and reinforcement learning are generally distinguished from one another. In supervised learning, the ML model is trained using a data set made up of pairs of inputs and outputs, or features and labels. The objective of supervised learning would be to identify patterns in the training data that may be used, for as when predicting the quality of a given product based on the manufacturing data. In unsupervised learning, the computer makes decisions based on data rather than on previously seen results. Instead, in order to be able to spot future anomalies, the algorithm learns, for instance, what usual sensor data from a machine looks like. [4] A so-called agent in reinforcement learning, the third type of ML, should operate in a way that maximises some idea of cumulative reward [5].

The potential uses for machine learning are as varied as its capabilities. Machine learning algorithms have always had the ability to anticipate the best time for repair work or tool replacements and can assess the state of machinery or tools when it comes to predictive maintenance [7,8]. As a result, quality controls like verifying random samples are no longer essential [8,9]. Instead, ML-based models may be employed in quality management to evaluate or perhaps even forecast the product's quality terms of process information. It is anticipated that using ML in process control will increase flexibility to changing conditions, stabilise output quality, and concurrently lower reject rates [7,10]. Recent developments in ML-based object identification and motion planning have produced significant advancements, particularly in the field of robotics [11].

III.MACHINE LEARNING APPLICATIONS IN THE MANUFACTURING

A study on inductive learning is given in this section's study of certain machine learning applications in the industrial sector. Inductive learning is the main topic since in-depth analyses of the other methods may be obtained elsewhere. [12-13]

Algorithms for machine learning are independent of domain. They may, in theory, be a very helpful tool when building knowledge-based systems. The use of machine learning techniques follows a predictable trend. Formulating the issue, deciding on the representation, gathering training data, assessing the information learnt, and fielding the knowledge base are the method' primary steps [14-16]

Machine-learning methods may be effective tools for identifying important patterns in data. Since there are no approaches that can be used in all situations, it is essential to recognize the specifications of a given problem and select the strategy that aim to satisfy specific specifications.

Machine learning has been effectively used to a broad variety of manufacturing areas. Utilizing the findings of a simulation experiment, Lu and Chen [17] devised an inductive learning strategy and utilised it to create a qualitative knowledge base. Inductive learning was employed to build a generalised description over the values of the control parameters given a class (specified by the values of the class objective parameters). By doing this, the knowledge base that was created may be utilised to regulate the process using deductive reasoning.

Inductive learning was used by Stirling and Buntime [18] to look at issues with process-planning decision-making. They used a combination of expert interviews and induction to learn about the processing paths of a steel plant. The use of rule induction as a tool to aid the experts in formalising and organising their knowledge allowed for significant time and effort savings despite the fact that the experts were pretty articulate.

Engineers have used inductive learning techniques to synthesise vast volumes of data to aid in decision-making. Data from turning-process simulations were analysed using an inductive learning approach to enhance manufacturing machine operation planning [19].

A knowledge-processing technique that combines the strength of engineering simulation and optimization with inductive learning was published by Lu et al. [20]. Multi-objective optimization was combined with the inductive-learning technique to create a system that offers engineers flexible support throughout the model development and use phases.

The development of automated scheduling systems is crucial for production-operations management as the production phases grow more intricate. One of the practical approaches used to address this issue is learning-based scheduling, which involves the automated acquisition of dispatching rules. There have been several initiatives to apply learning to scheduling issues [21–26]. Flow-shop scheduling issues [27–31], jobshop scheduling issues, and flexible manufacturing systems scheduling issues were all addressed utilising the suggested approaches for learning scheduling rules using inductive learning techniques. Applying the suggested strategies, according to experimental results, can lead to efficient scheduling.

To uncover relevant design knowledge, Zhou et al. [32] created an intelligent datamining system and used it to analyse drop-testing data of portable electronic items. The C4.5 algorithm is the basis of the rule-induction technique used. Studies using the suggested method showed that its strategy is adaptable and may be used to save costs and boost productivity in a variety of other design and production processes.

A system for industrial visual inspection that may be applied to quality control for mass production was presented by Aksoy et al. [33]. The RULES-3 algorithm for inductive learning is used by the system.

Peng [34] created a fuzzy inductive learning-based intelligent monitoring system to increase the dependability of industrial operations. In order to assure the calibre of the tapping procedures, the approach was effectively used to diagnose their problems. The technique was successfully used to assess the state of the tapping procedures in order to guarantee product quality.

IV. INFLUENCE OF MACHINE LEARNING ON MANUFACTURING AND INDUSTRY 4.0 DOMAIN

A. Fault Detection

Reduced machine downtime helps manufacturing organisations compete effectively by allowing for prompt and accurate detection of industrial equipment process issues. As an increasing number of clients want manufacturers to accelerate the process of delivering high-quality products at a cheap cost, machine learning algorithms in the manufacturing sector will see growing utilisation for allowing manufacturing system problem diagnosis.

Jian et al. [35] introduce a cloud edge-based two-level hybrid scheduling learning model in cloud manufacturing. According to the First-in First-out (FIFO) concept, the suggested model divides and allocates various scheduling jobs into a number of first-level sub - tasks at the top level. The second level permits even more precise deconstruction into atomic jobs which are later assigned to various industrial machinery (factory edge nodes). The second level solves scheduling issues using a novel VSSBA (enhanced bat algorithm) as well as LSTM (long and short-term memory networks) combination. The researchers' experiments demonstrate that the two-level method can enhance performance in practical applications in a cloud manufacturing environment.

A transfer learning approach based on deformable CNN-DLSTM for defect identification of rolling bearings under various operation circumstances A transfer learning-based method for combining deformable convolutional neural network (CNN) and deep long short-term memory (DLSTM) rolling bearing failure diagnostics is presented by Wang et al [36]. In areas where it is challenging to locate appropriate large-scale labelled data, the authors explicitly concentrate investigating bearing failures during diverse operating situations. They may pre-train a defect diagnostic model utilizing data samples underneath one operating environment and then move the model with additional finetuning (with relatively few data samples) to some other working state using the transfer learning technique. When used on an experimental data set, the created framework outperforms state-of-the-art techniques. The article "Applications of deep learning for fault identification in industrial cold forging" [37] by Glaeser et al. demonstrates the utilization of deep learning methods in the fault diagnosis domain of manufacturing cold forging. In order to comprehend how machine signal influenced various defects, the researchers specifically explain two separate ways based on convolutions neural network (CNN) and decision tree (DT). Considering vibration testing data sets gathered for frequently occurring defects in the industrial cold forging arena, several techniques described here perform better.

B. Inspection and Surveillance using Computer Vision

Computer vision-based part inspection and process monitoring is one of the industrial domain's most high-impact application areas for machine learning. High throughput part inspection may be made possible by using inexpensive sensors like RGB cameras combined with ML-based algorithms. Monitoring a product throughout the whole manufacturing process is possible with computer vision (images and video) based technologies that are combined with ML. Furthermore, a computer vision-based strategy can also provide excellent continuous process monitoring.

Zhang and Gao's paper "Soft sensor of flotation froth grade classification based on hybrid deep neural network" [38] summarises their efforts to create a soft sensor that can analyse froth pictures of flotation tailing to classify the grade of iron ore tailings. The creation of a database of froth photographs of flotation tailings and a comparison of the efficacy of several deep neural network (DNN) models for the job at hand are indeed the paper's two main findings. The researchers construct software around a fine-tuned DNN model that has great accuracy based on the analysis outcomes. The experimental findings demonstrate the possibility for using DNNs in the iron ore froth flotation industry.

A data-driven technique for allowing automated evaluation of integrated circuit (IC) wire bonding faults is presented in "A data-driven way of improving the image-based automatic inspection of IC wire bonding defects" by Chen et al. [39] The approach described in the research consists of three steps: (1) data pre-processing to find and separate IC chip image patches from the raw picture; (2) feature engineering to extract geometric features from the segmented wires; and (3) machine learning methods (such as CNN and SVM) dependent categorization. The authors use a series of X-ray pictures obtained out of a semiconductor foundry to demonstrate the effectiveness of the established approach.

C. Process Optimization and Enhancement

The prescriptive analytics capability of ML approaches may support the efforts of manufacturing staff to choose the ideal combination of parameters connected with a specific manufacturing process, allowing industrial process enhancement and optimization. In the upcoming years, there will be tremendous development in the field at the nexus of machine learning and process optimization that produces industrial analytics insights that allow speedy bulk and personalized manufacturing capacity with the least amount of waste straightforward.

The article "A supervised machine learning method for the optimization of the assembly line feeding mode selection" by Zangaro et al. [40] describes a supervised learning-based strategy for optimizing use of the classification and regression tree (CART) algorithms for the line feeding problem (LFP). The suggested method uses the production environment and component properties as feed to build a decision tree which thus offers a line feeding technique for each component. They also define a repair strategy that offers viable options with tolerable average cost deviations for situations that lead to an infeasible solution. The suggested method accurately predicts the line feeding mode with respect to categorization.

Rnsch, Kulahci, and Dybdahl reveal their research on the study that examines the efficient usage of data from different sources for process improvement in injection moulding in their article titled "An investigation of the utilisation of different data sources in manufacturing with application in Injection Moulding" [41]. The researchers specifically examine regardless of wether additional sensor signals obtained at a greater price might provide more useful data but whether a high predictive accuracy can sometimes be attained by using widely accessible Machine Process Data on a moulding manufacturing line consisting of 100 injection moulding machines. They reached the conclusion that perhaps the variability inside the raw resources that affects element quality is not captured by the machine data processing for the specific use case that was carried out in close cooperation with an industrial partner.

The research "Using process mining to increase productivity in make-to-stock manufacturing" by Lorenz et al. [41] demonstrates an unique application case using datadriven method to improve productivity in make-tostock industrial production. In particular, the described approach makes use of process mining to automatically dynamically map and analyse industrial processes with high levels of complexity and variation. This enables productivity improvement. A testing phase from a top producer of sanitary items is used by the authors to experimentally evaluate the utilisation of the created technique, plus they offer concrete improvement recommendations for such makers.

V. ADVANTAGES OF APPLYING MACHINE LEARNING TOWARDS MANUFACTURING

ML approaches are able to solve NP complete issues, which frequently arise when it comes to optimization challenges of intelligent manufacturing systems, which is one of the general advantages of ML that has been demonstrated in earlier sections [43].

The following focuses on how machine learning approaches may manage high-dimensional, multi-variate data and uncover implicit associations from big data sets in an environment that is dynamic, chaotic, and frequently complicated [44].

Due to the fact that "the majority of engineering and industrial issues are data-rich but knowledge-sparse" (Lu, 1990), ML offers a method to improve domain knowledge. The benefits are discussed in this section in an effort to generalise them to ML as a whole. It must be remembered, nonetheless, that the peculiarities of the benefits may vary depending on the ML approach selected.

The greater usefulness of application of algorithms made possible by (sometimes open source) applications like Rapidminer is another benefit of ML approaches. This enables (relatively) simple use in various situations and, in addition, convenient parameter tweaking to improve classification performance.

As was already said, one of the main benefits of ML algorithms is their ability to find previously undiscovered (hidden) information and implicit correlations in data sets. The demands on the supplied data may change depending on the feature of the machine learning method (supervised/unsupervised, or Reinforcement Learning [RL]). However, several studies have successfully demonstrated the general capacity of machine learning algorithms to provide results in a manufacturing context [45-48]

The capacity of ML algorithms to handle large dimensional issues and data is a benefit. This will probably become even more crucial in the future, particularly in light of the growing accessibility of complicated data [49] and the lack of transparency in manufacturing [50]. This cannot be generalised, as is true for the majority of ML algorithm benefits and drawbacks. High dimensionality may be handled by some algorithms (like SVM and Distributed Hierarchical Decision Tree) better than others [51-52]. As previously said, the majority of ML algorithms that can handle high-dimensional data are useful in manufacturing. Therefore, one benefit of ML use in manufacturing is the capacity to handle large dimensionality.

Applying ML in manufacturing may lead to the extraction of patterns from already-existing data sets, which may serve as a foundation for the creation of estimates about the system's future behaviour [53,54]. The process owners' decision-making may be assisted by the new information, or the system itself may be directly improved. Ultimately, the objective of several ML approaches is to find specific patterns or regularities that characterise interactions [54].

According to their unique performance in industrial applications by several parameters, Kotsiantis (2007) compared a number of algorithms. Each problem is unique, and each algorithm's performance also depends on the data that is accessible, the data that has been processed, and the parameter settings [55].

VI. CHALLENGES IN THE MANUFACTURING INDUSTRIES

Even though the manufacturing sector is well-established, its significance cannot be overstated. Over the past several decades, the manufacturing sector's contribution to the GDP of some developed nations has decreased. However, a number of measures to revitalise the industrial base were undertaken in recent times.

The difficulties that manufacturing is currently facing are distinct from those of the past.

The continued trend of the manufacturing sector becoming more complicated and dynamic is shown by these major difficulties. In addition to the manufacturing plans themselves, the product that will be made as well as the (business) procedures of the enterprises and collaborative networks progressively inherit the seeming complexity [56].

There are various research studies that outline the major difficulties faced by manufacturing on a worldwide scale. According to several researchers [57-60].

The following are the main challenges [57-60]:

1) Using cutting-edge manufacturing technology
2) Growing significance of high-value-added product production.
3) Making use of cutting-edge knowledge, data management, and AI technologies.
4) Products and production (processes) that are sustainable.
5) Enterprise capabilities and supply chains that are agile and adaptable.
6) Innovation in goods, services, and business practises.
7) To implement new technology, industry and research work closely together.
8) New production management paradigms

The continued trend of the manufacturing sector becoming more complicated and dynamic is shown by these major difficulties. In addition to the manufacturing plans themselves, the product that will be made as well as the (business) procedures of the enterprises and collaborative networks progressively inherit the seeming complexity [56]. The dynamic business environment that today's industrial businesses operate in is influenced by uncertainties, which heightens the difficulty [61].The increasing availability of data is adding a new challenge, especially when considering domains that are most likely to be optimised, such as monitoring and management, work schedules, and diagnostic tests: in addition to the large amounts of available data (such as sensor data), the high dimensionality and wide range of information as well as the NP-complete nature of manufacturing optimization problems present a new challenge. Valid candidates for solving some of the current complex industrial systems' biggest problems are machine learning approaches. These data-driven methodologies are capable of identifying very intricate and non-linear patterns in data from many sources and data kinds, and they can also convert raw data into feature spaces, or models, which may subsequently be used for forecasting, detection, classifying, regression, or prediction.

VII. CONCLUSIONS

As machine learning techniques are integrated and used, industrialization is undergoing a significant transformation. In in order to comprehend and analyse this transformation at the start of this decade, this special issue managed to bring together a vast scope of research studies to review the most recent work in the fundamental theoretical as well as experimental aspects of Machine Learning and their implementations in production systems and manufacturing systems.

These papers in this special issue cover a wide range of issues, including computer-vision derived inspection and tracking flaw detection, cloud manufacturing, continuous improvements and optimization, and thorough top of the line literature review. A wide range of practical manufacturing applications clearly benefit greatly from machine-learning techniques. Today, several of businesses across the globe offer business implementations of these algorithms, effective connections to commercial databases, and attractive user interfaces. These approaches do, however, have significant drawbacks. The methods shown here allow for reasonably quick mining of data sets including tens of thousands of training occurrences. However, many relevant data sets are a lot bigger.

It's also crucial to remember that the physics underlying the physical events may be used to complement ML-based decision-making in industrial applications. Combining ML with physics is essential, especially for industrial applications where data gathering could be costly and risky. The majority of the machine learning techniques now in use for creating multiple models may greatly boost accuracy compared to single models, but at the sacrifice of comprehension. Therefore, obtaining ensemble classifiers that are simple to interpret is an essential area of research.

The applications for machine learning, particularly in manufacturing, will continue to grow quickly due to quick advances in the field of algorithms, growing data availability (thanks, for example, to low-cost sensors and the trend toward smart manufacturing), and increased computing power. As of right now, supervised algorithms prevail in the majority of manufacturing-related applications. However, unsupervised approaches (including RL) may become more significant in the future because to the quick growth in data availability, which is caused by better and more sensor technologies as well as higher awareness. Hybrid strategies that provide "the best of both worlds" are already in use. This is consistent with the current media emphasis given to breakthroughs in big data.

In conclusion, it is safe to say that ML is already a potent tool for many applications within (intelligent) industrial systems and smart manufacturing, and that its significance will only grow in the future. Since cooperation between several disciplines, such as Computer Science, Industrial Engineering, Mathematics, and Electrical Engineering is required to drive advancement, it poses both a huge potential and a sizable danger.

REFERENCES

[1] Wissenschaftliche Gesellschaft für Produktionstechnik e.V. WGPStandpunkt Industrie 4.0. Darmstadt: WGP; 2016.
[2] Chen Y. Integrated and Intelligent Manufacturing: Perspectives and Enablers. Engineering 2017;3(5):588–95.
[3] Samuel AL. Some Studies in Machine Learning Using the Game of Checkers. IBM J. Res. Dev. 1959;3(3):211–29.
[4] Hastie T, Tibshirani R, Friedman JH. The elements of statistical learning: Data mining, inference, and prediction. 2nd ed. New York NY: Springer; 2009.
[5] Sutton RS, Barto AG. Reinforcement learning: An introduction. Cambridge, Mass.: MIT Press; 20]10.
[6] Witten IH, Frank E, Hall MA, Pal CJ. Data Mining: Practical Machine Learning Tools and Techniques. 4th ed. Cambridge: Morgan Kaufmann; 2017.
[7] VDMA Software and Digitalization. Quick Guide - Machine Learning in Mechanical and Plant Engineering; 2018.
[8] Choudhary AK, Harding JA, Tiwari MK. Data mining in manufacturing: a review based on the kind of knowledge. J. Intell. Manuf. 2009;20(5):501–21.
[9] Lenz J, Wuest T, Westkämper E. Holistic approach to machine tool data analytics. J. Manuf. Syst. 2018;48:180–91.
[10] Mayr A, Weigelt M, Masuch M, Meiners M, Hüttel F, Franke J. Application Scenarios of Artificial Intelligence in Electric Drives Production. Procedia Manuf. 2018;24:40–7.
[11] iit – Institut für Innovation und Technik in der VDI/VDE Innovation + Technik GmbH. Potential of Artificial Intelligence in Germany's Producing Sector; 2018.
[12] Monostori, L. AI and machine learning techniques for managing complexity, changes and uncertainties in manufacturing. Engng Appl. Artific. Intell., 2003, 16(3), 227–291.
[13] Monostori, L., Ma´rkus, A., Van Brussel, H., and Westka¨mper, E. Machine learning approaches to manufacturing. CIRP Annals, 1996, 45(2), 675–712.
[14] Langley, P. and Simon, H. A. Applications of machine learning and rule induction. Commun. ACM, 1995, 38(11), 55–64.
[15] Braha, D. Data Mining for Design and Manufacturing: Methods and Applications, 2001 (Kluwer Academic Publishers, Boston, MA).
[16] Lavracˇ, N., Motoda, H., Fawcett, T., Holte, R., Langley, P., and Adriaans, P. Introduction: lessons learned from data mining applications and collaborative problem solving. Mach. Learn., 2004, 57, 13–34.
[17] Lu, S. C.-Y. and Chen, K. A machine learning approach to the automatic synthesis of mechanistic knowledge for engineering decision making. Artif. Intell. Engng Des. Anal. and Mfg 1987, 1(2), 109–118.
[18] Stirling, D. and Buntine, W. Process routing in a steel mill: A challenging induction problem. In Artificial Intelligence Developments and Applications (Eds J. S. Gero and R. Stanton), 1988, pp. 301–313 (Elsevier Science Publisher B.V., North-Holland).
[19] Whitehall, B. L., Lu, S. C.-Y., and Stepp, R. E. CAQ: a machine learning tool for engineering. Artif. Intell. Engng, 1990, 5(4), 189–198.

[20] Lu, S. C.-Y., Tcheng, D. K., and Yerramareddy, S. Integration of simulation, learning and optimisation to support engineering design. Annals CIRP, 1993, 38(1), 143–146.

[21] Aytug, H., Bhattacharyya, S., Koehler, G. J., and Snowdon, J. L. A review of machine learning in scheduling. IEEE Trans. Engng Mgmt, 1994, 41(2), 165–171.

[22] Aytug, H., Koehler, G. J., and Snowdon, J. L. Genetic learning of dynamic scheduling within a simulation environment. Comput. Op. Res., 1994, 21, 909–925.

[23] Jain, A. S. and Meeran, S. Job-shop scheduling using neural networks. Int. J. Prod. Res., 1998, 36(5), 1249– 1272.

[24] Priore, P., Fuente, D., Gomez, A., and Puente, J. Dynamic scheduling of manufacturing systems with machine learning. Int. J. Found. Comput. Sci., 2001, 12(6), 751–762.

[25] Akyol, D. E. Application of neural networks to heuristic scheduling algorithms. Comp. Indust. Engng, 2004, 46, 679–696.

[26] Pierreval, H. and Ralambondrainy, H. A simulation and learning technique for generating knowledge about manufacturing systems behaviour. J. Op. Res. Soc., 1990, 41(6), 461–474.

[27] Nakasuka, S. and Yoshida, T. Dynamic scheduling system utilising machine learning as a knowledge acquisition tool. Int. J. Prod. Res., 1992, 30(2), 411–431.

[28] Suwa, H., Fujii, S., and Morita, H. Heuristic rule acquisition for flow-shop scheduling. In Proceedings of the 1996 Japan–USA Symposium on Flexible Automation, Kobe, Japan, 1996, 1345–1351.

[29] Suwa, H., Fujii, S., and Morita, H. An acquisition of scheduling rules for flow-shop problems. In Proceedings of the 6th IFIP TCS/WG5.7 International Conference on Advances in Production Management System, Japan, 1996, 631–636.

[30] Koonce, D. A., Fang, C., and Tsai, S. A data mining tool for learning from manufacturing systems. Comput. Indust. Engng, 1997, 33(1–2), 27–30.

[31] Murata, T., Sugimoto, T., Tsujimura, T., and Gen, M. Rule conversion in knowledge acquisition for flow shop scheduling problems. In Proceedings of the Joint 9th International Fuzzy Systems Association (IFSA) World Congress and 20th North American Fuzzy Information Processing Society (NAFIPS) International Conference, Vancouver, Canada, 2001, 4, 2417–2421.

[32] Zhou, C., Nelson, P. C., Xiao, W., Tirpak, T. M., and Lane, S. A. An intelligent data mining system for drop test analysis of electronic products. IEEE Trans. Electr. Packag. Mfg, 2001, 24(3), 222–231.

[33] Aksoy, M. S., Torkul, O., and Cedimoglu, I. H. An industrial visual inspection system that uses inductive learning. J. Intell. Mfg, 2004, 15, 569–574.

[34] Peng, Y. Intelligent condition monitoring using fuzzy inductive learning. J. Intell. Mfg, 2004, 15, 373–380.

[35] Jian, Chengfeng, Jing Ping, and Meiyu Zhang. 2020. "A cloud edge-based two-level hybrid scheduling learning model in cloud manufacturing." International Journal of Production Research. doi:10.1080/00207543.2020.1779371.

[36] Wang, Zheng, Qingxiu Liu, Hansi Chen, and Xuening Chu. 2020. "A deformable CNN-DLSTM based transfer learning method for fault diagnosis of rolling bearing under multiple working conditions." International Journal of Production Research. doi:10.1080/00207543.2020.1808261

[37] Glaeser, Andrew, Vignesh Selvaraj, Sooyoung Lee, Yunseob Hwang, Kangsan Lee, Namjeong Lee, Seungchul Lee, and Sangkee Min. 2021. "Applications of deep learning for fault detection in industrial cold forging." International Journal of Production Research. doi:10.1080/00207543.2021.1891318

[38] Zhang, Dingsen, and Xianwen Gao. 2021. "Soft sensor of flotation froth grade classification based on hybrid deep neural network." International Journal of Production Research. doi:10.1080/00207543.2021.1894366

[39] Chen, Junling, Zijun Zhang, and Feng Wu. 2020. "A data driven method for Enhancing the image-based automatic inspection of IC wire bonding defects." International Journal of Production Research. doi:10.1080/00207543.2020.1821928.

[40] Zangaro, Francesco, Stefan Minner, and Daria Battini. 2020. "A supervised machine learning approach for the optimization of the assembly line feeding mode selection." International Journal of Production Research. doi:10.1080/00207543.2020. 1851793.

[41] Rønsch, G., M. Kulahci, and M. Dybdahl. 2021. "An investigation of the utilisation of different data sources in manufacturing with application in Injection Moulding." International Journal of Production Research. doi:10.1080/00207543.2021. 1893853.

[42] Lorenz, Rafael, Julian Senoner, Wilfried Sihn, and Torbjørn Netland. 2021. "Using process mining to improve productivity in make-to-stock manufacturing." International Journal of Production Research. doi:10.1080/00207543.2021.1906460.

[43] Monostori, L., Hornyák, J., Egresits, C., & Viharos, Z. J. (1998). Soft computing and hybrid AI approaches to intelligent manufacturing. Tasks and Methods in Applied Artificial Intelligence Lecture Notes in Computer Science, 1416, 765–774. doi:http://dx.doi.org/10.1007/3-540-64574-8_463

[44] Köksal, G., Batmaz, İ., & Testik, M. C. (2011). A review of data mining applications for quality improvement in manufacturing industry. Expert Systems with Applications, 38, 13448–13467. doi:http://dx.doi.org/10.1016/j.eswa.2011.04.063

[45] Alpaydin, E. (2010). Introduction to machine learning (2nd ed.). Cambridge, MA: MIT Press.

[46] Filipic, B., & Junkar, M. (2000). Using inductive machine learning to support decision making in machining processes. Computers in Industry, 43, 31–41. doi:http://dx.doi.org/10.1016/S0166- 3615(00)00056-7

[47] Guo, X., Sun, L., Li, G., & Wang, S. (2008). A hybrid wavelet analysis and support vector machines in forecasting development of manufacturing. Expert Systems with Applications, 35, 415–422. doi:http://dx.doi.org/10.1016/j.eswa.2007.07.052

[48] Kim, D., Kang, P., Cho, S., Lee, H., & Doh, S. (2012). Machine learning-based novelty detection for faulty wafer detection in semiconductor manufacturing. Expert Systems with Applications, 39, 4075–4083. doi:http://dx.doi.org/10.1016/j.eswa.2011.09.088

[49] Yu, L., & Liu, H. (2003). Feature selection for high-dimensional data: A fast correlation-based filter solution. In Proceedings of the Twentieth International Conference on Machine Learning (ICML2003) (pp. 8). Washington, DC

[50] Smola, A., & Vishwanathan, S. V. N. (2008). Introduction to machine learning. Cambridge: Cambridge University Press

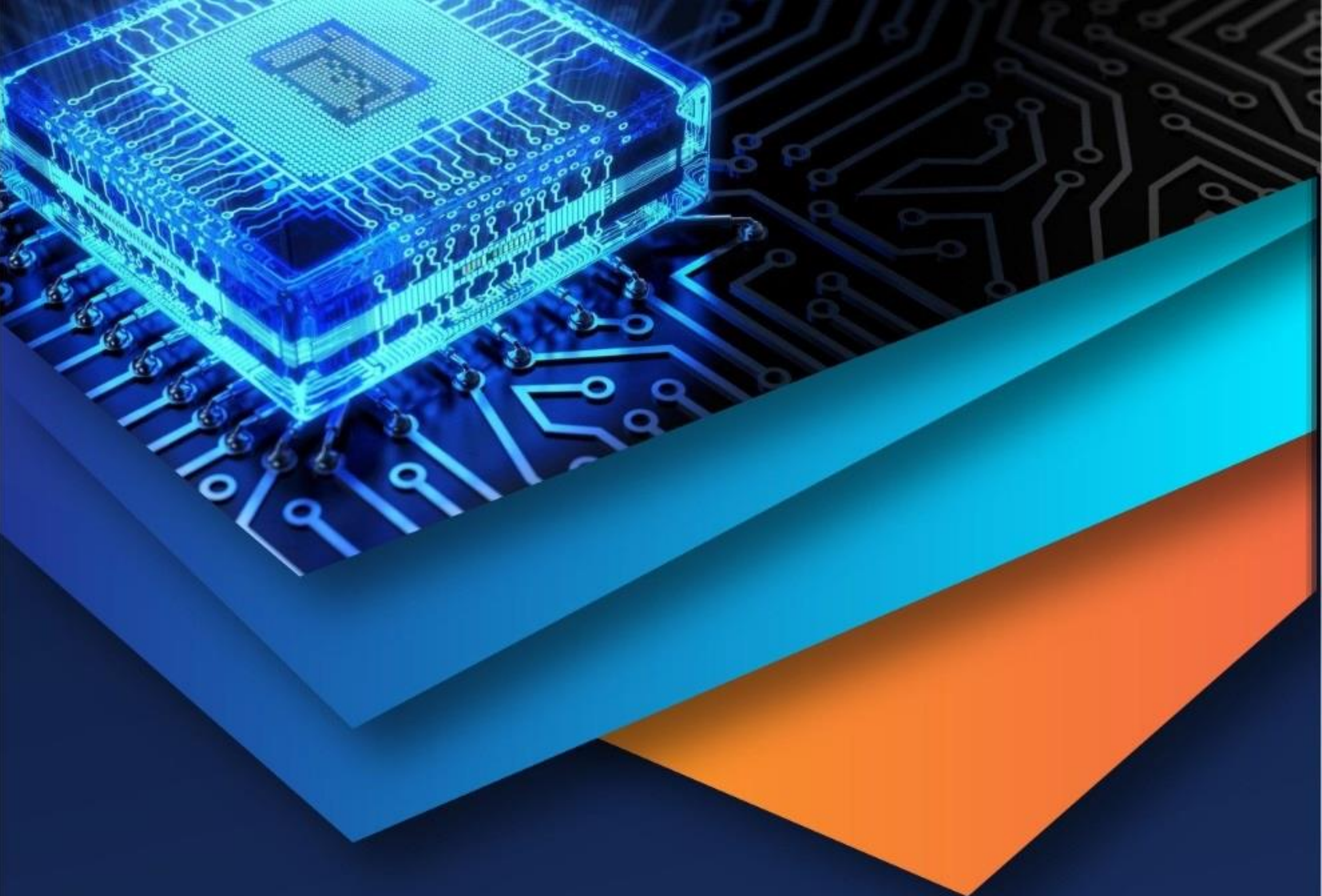
[51] Bar-or, A., Schuster, A., Wolff, R., & Keren, D. (2005). Decision tree induction in high dimensional, hierarchically distributed databases. In Proceedings SI-AM International Data Mining Conference (pp. 466–470). Newport Beach, CA.

[52] Do, T.-N., Lenca, P., Lallich, S., & Pham, N.-K. (2010). Classifying very-high-dimensional data with random forests of oblique decision trees. In F. Guil-let, G. Ritschard, D. Zighed, & H. Briand (Eds.), Advances in knowledge discovery and management (pp. 39–55). Berlin: Springer

[53] Alpaydin, E. (2010). Introduction to machine learning (2nd ed.). Cambridge, MA: MIT Press.

[54] Nilsson, N. J. (2005). Introduction to machine learning. Stanford, CA.

[55] Kotsiantis, S. B. (2007). Supervised machine learning: A review of classification techniques. Informatica, 31, 249–268.
[56] Wiendahl, H.-P., & Scholtissek, P. (1994). Management and control of complexity in manufacturing. CIRP Annals, 43, 533–540. doi:http://dx.doi.org/10.1016/S0007-8506(07)60499-5
[57] Dingli, D. J. (2012). The manufacturing industry – Coping with challenges (Working Paper No. 2012/05). Maastricht: Maastricht School of Management.
[58] Gordon, J., & Sohal, A. S. (2001). Assessing manufacturing plant competitiveness. International Journal of Operations & Production Management, 21, 233–253.
[59] Shiang, L. E., & Nagaraj, S. (2011). Impediments to innovation: Evidence from Malaysian manufacturing firms. Asia Pacific Business Review, 17, 209–223. doi:http://dx.doi.org/10.1080/13602 381.2011.533502
[60] Thomas, A. J., Byard, P., & Evans, R. (2012). Identifying the UK's manufacturing challenges as a benchmark for future growth. Journal of Manufacturing Technology Management, 23, 142–156. doi:http://dx.doi.org/10.1108/17410381211202160
[61] Monostori, L. (2003). AI and machine learning techniques for managing complexity, changes and uncertainties in manufacturing. Engineering Applications of Artificial Intelligence, 16, 277–291. doi:http://dx.doi.org/10.1016/S0952-1976(03)00078-2



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY