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Optimization of Manufacturing Processes using Artificial Intelligence and Machine Learning

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Making frameworks involves dealing with constantly complex, dynamic, and occasionally even turbulent behaviour. Utilizing all available ways is essential to having the choice to efficiently satisfy the desire for outstanding things. Machine learning is one area where promising results and convenience have seen rapid developments. Problematic new developments include added substance manufacture (AM) and artificial intelligence (simulated intelligence). AM has not yet embraced the fact that artificial intelligence plays a vital role in many facets of our lives. A "shrewd" invention is shown using a wide range of data and endless machine learning calculations for the benefit of scientific expectation. The analysis supports the application of shrewd management and prompt response to changes in a manufacturing cycle. The methodology suggested in the research applies the disappointment mode, impact investigation, and calculation for profound learning to improve a mechanical manufacturing line for electronic parts. This method is incorporated into a product device created using the Windows Structures innovation and open source to aid in the identification of the anticipated risks by the reliable designer.

Keywords: Optimization, Manufacturing, Artificial Intelligence, Machine Learning.

1. Introduction

The availability of information is increasing at a never-before-seen rate in the manufacturing industry today. These data include a variety of organizations, meanings, and qualities, such as sensor data from the production line, natural data, machine device limits, and so forth. Large Information is a term that is frequently used to refer to the growth and accessibility of a lot of information [1]. The ability to easily obtain information about quality, for instance, provides opportunity to logically enhance cycle and item quality. In any event, it has been noted that an abundance of data can also be proposed as a test and may lead to undesirable outcomes, such as deviating from the primary issues or causalities or delaying or resulting in incorrect conclusions regarding appropriate actions. The manufacturing industry must acknowledge that, while it generally tends to be finished securely, support is required to handle the high dimensionality, complexity, and components involved if it is to benefit from the expanded information accessibility, such as for quality improvement drives, manufacturing cost assessment and additionally process optimization, better understanding of the client's needs, etc.

Machine learning (ML), which gives manufacturing the abilities it needs for greater adaptability and versatility, is one of the foundations for making manufacturing (more) intelligent. These advances in machine learning are changing conventional manufacturing into Industry 4.0's intelligent manufacturing [2]. A few examples of computerized arrangements and trend-setting innovations that have a big impact on the manufacturing industry include the Modern Web of Things (IIoT), added substance manufacturing, advanced twins, high level mechanical technology, distributed computing, and expanded/augmented experience. An area of Artificial Intelligence (computer-based intelligence) that deals with calculations that learn directly from their feedback data is known as "machine learning" (ML). Attempts have been made in the past to determine the whole scope of machine learning in manufacturing, despite the fact that the majority of specialists concentrate on identifying a single effective machine learning solution to a specific problem. Wang et al. (2018) described employing machine learning calculations on a periodic basis together with an evaluation of their applications to make manufacturing "savvy." They discussed four learning models in particular: Convolutional Brain Organizations, Confined Boltzmann Machines, Auto-Encoders, and Repetitive Brain Organizations. Additionally, they offered a classification based on application spaces for both contemporary regions and cycles, as well as their particular subareas. The most often employed computations, Brain Organizations (NNs), Backing Vector Machine (SVM), and Tree-Based (TB) approaches, were among the many patterns the authors examined in relation to administered, individual, and built-up learning procedures in these fields. A second literary assessment by Dogan and Birant aimed to give readers a comprehensive understanding of the key strategies and calculations from the fields of machine learning (ML) and data mining (DM) that have recently been applied to progress manufacturing.

Simulated intelligence can be categorized into two different approaches: computational intelligence and emblematic or traditional intelligence. Computational intelligence involves handling problems and making decisions in light of model data [3]. According to the IEEE Computational Intelligence Society, artificial brain organization, fluffy frameworks, and developmental programming are all examples of computational man-made intelligence.

Through various techniques, such as machine learning (ML), it is possible to acquire both symbolic and computational intelligences through analyses and replications. Simulated intelligence includes subfields like mechanized thinking, in which computer programs are used to give robots the ability to fully or virtually fully reason and act. The machine's justifications or justifications may frequently need to be made in the face of uncertainty. Making decisions in these circumstances is unquestionably a probabilistic rather than a deterministic activity, and as a result, complex areas of fuzzy logic and Bayesian measures can be quite useful in determining them.

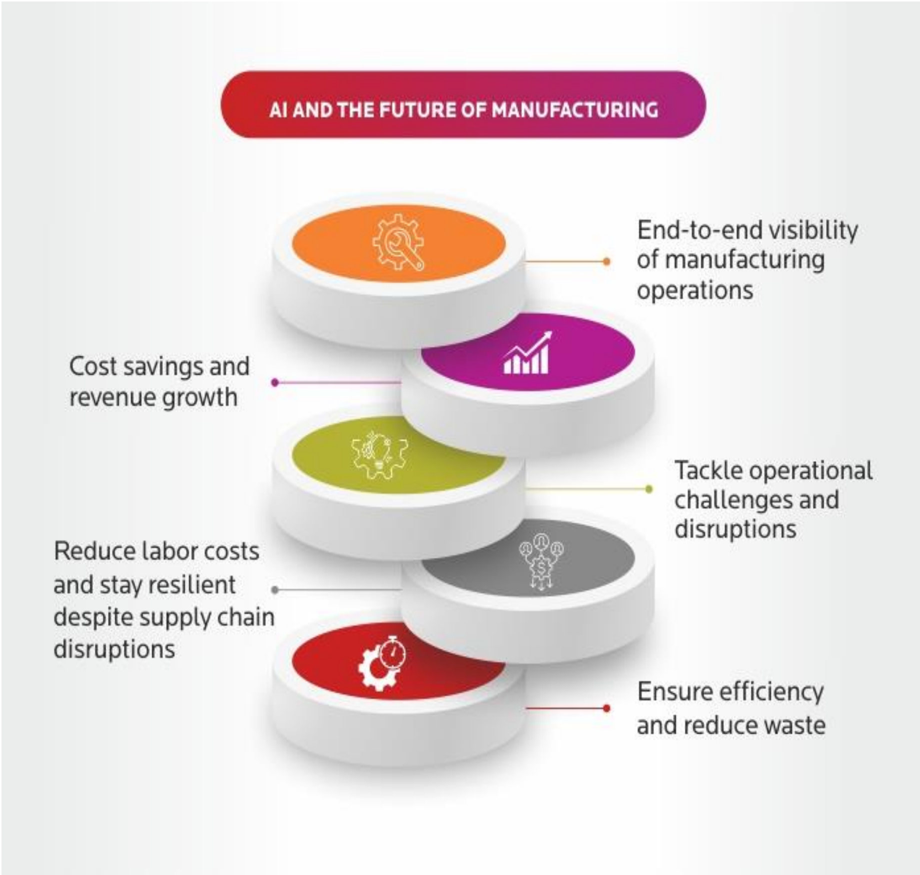

Figure 1: The Future of Manufacturing with AI

2. Literature Review

In the Diary of Manufacturing Innovation, Johnson (2020) investigates the optimization of manufacturing processes using computer-based intelligence and ML [4]. the directors. The article provides a summary of the many techniques used in manufacturing process optimization, including fuzzy logic, hereditary calculations, and brain organization. The author highlights the anticipated benefits of ML and AI in enhancing manufacturing productivity, quality, and efficiency.

The Diary of Canny Manufacturing by Li, Wang, and Zhang (2021) provides a thorough analysis of computer-based intelligence and machine learning applications in manufacturing process improvement. The authors discuss numerous methods for enhancing industrial processes, including support learning, support vector machines, and Bayesian organizations [5]. They look at the benefits, challenges, and potential implications of applying ML and AI to various aspects of production.

In the PCs in Industry diary, Zhang, Chen, and Cao (2022) explore the application of profound support learning (DRL) for the optimization of industrial processes [6]. The evaluation suggests a framework to modernize intricate production frameworks by fusing DRL calculations with re-enactment models. The creators demonstrate the effectiveness of DRL in raising creation productivity and lowering energy use.

In the Mechanical Technology and PC Coordinated Manufacturing journal, Gupta, Nandi, and Beam (2023) provide an investigation study on continuous optimization of manufacturing processes involving computer-based intelligence and ML approaches. To advance manufacturing processes, the designers offer a clever framework that coordinates machine learning calculations with ongoing information analysis [7]. They emphasize the importance of adaptable optimization strategies for dealing with uncertain and changing industrial environments.

The focus of Singh and Saxena (2023) is on the development of a cleverly chosen, mutually beneficial network for the optimization of manufacturing processes in the Global Diary of Creation Exploration [8]. The paper suggests a structure for handling optimization that makes use of artificial intelligence (AI) and machine learning (ML) techniques, such as fluffy reasoning, brain organizations, and master frameworks. The framework's suitability for improving creation execution and cutting expenses is demonstrated by the framework's designers.

3. AI And ML Applications in Post Process

Very little machine learning and artificial intelligence has been used in AM's post-processing procedures. Because the parts have already been manufactured and the opportunity for in-place management and improvement has already passed, this is the case at the post-cycle stage. To speed up the procedure for next forms, data gathered after handling can be utilised. However, there are times when quality characteristics, such as the depth of flaws, the roughness of the surface, or the number of layers of precision, and dependability characteristics, such as the strength of the weak point, can be linked to the underlying design, raw materials, or cycle circumstances. Cyclic mechanical or thermo-mechanical fatigue is a key factor in dependability for the vast majority of AM applications [9]. For instance, high temperature components used in stream motors, which frequently face cyclic load, frequently encounter fatigue disappointment. Fatigue becomes a significant concern as added material AM is increasingly used in aviation applications. In order to improve the materials' long-term behavior as a capability of interaction boundaries, a few experts have attempted to apply ML. To determine the exhaustion strength of tempered steel utilizing writing data, for instance, a modular neuro-fluffy derivation framework was created. In light of fictitious models and various deformities created during AM operations, several studies concentrated on fatigue forecasting for additive manufacturing parts using machine learning.

The microstructure of the parts and the many manufacturing faults, like porosity and surface deformities, affect how long the parts will last in an exhaust system. The use of powder bed techniques frequently has these kinds of issues. The examination of porosity as a cycle quality file was the subject of a few research. X-beam tomography is frequently used to gauge porosity and defect thickness. At the post-cycle level, the majority of exams have been concentrated on using machine learning (ML) calculations to enhance the age and optimization of x-ray tomography images and their comprehension. More care was taken in a study where the preparatory hotspot for the ML calculation of the order of porosity sorts was micrographs of metallic objects created using laser powder bed processes. In order to get beyond the limitations and expenses involved with utilizing in situ observation devices to improve the cycles, a study on quality repeatability concentrated on a factual analysis of the relationship between downstream mechanical qualities and the cycle inputs [10]. The key discovery was that the part area impact and post-chamber pressure drop together largely affected the mechanical properties of printed components.

There are advantageous prospects to employ ML in analysing these types of cycle outcomes given the significance of surface roughness and microstructural differences on the long-term performance of AM components. Surprisingly few researches have recently given attention to these viewpoints.

4. Research Methodology

The following strategies are incorporated into the examination philosophy: (1) To improve the manufacturing system for electronic parts using the robot FANUC-M-10, an analysis of the FMEA and its applications is carried out. The results are recorded in tables using data from experts. The behaviour As a demonstration model, part mounting is looked at in more detail. Informational collections are framed in light of the obtained data and are prepared for extra handling by a computation for profound learning. Datasets are arranged in accordance with the requirements of the.csv document. (2) A feed-forward artificial brain network with back-engineering is created in an effort to find the best brain network design in terms of the number of layers, the number of neurons in each layer, and the type of enactment capability. Testing informative indexes obtained using the past approach in the environment of RapidMiner Studio as a Machine Learning is applied at the proportion of preparing and testing information: 70%/30%. The findings of the FMEA are compared using machine learning. (3) A product instrument is planned and improved using C# programming, Windows Structures innovation, and open source solutions for the correlation of FMEA and scientific expectation.

THE FAILURE MODE AND EFFECT ANALYSIS

In order to accurately perform risk assessment in manufacturing when using a FANUC-M-10 robot to place and repair electronic components on a printed circuit board, the FMEA is chosen as the best method. The disappointment system suggests what is happening in a situation where a problem could arise. The problem is tied to mistakes, disappearances, or utter disappointments. The analysis of the outcomes of these anticipated problems is hinted at by the examination of the affects [11]. The severity of an issue's results, how frequently they occur, and how well they can be distinguished serve as indicators of its focus. The FMEA was created so that a few actions could be taken, starting with those that had the greatest need, to eliminate or reduce disappointments. FMEA is used to prevent mistakes, deformities, and disappointments that could occur during production. Pre-defined problems at the earliest possible stage of the creation engagement can thereby save resources, time, and materials. The benefits of FMEA include the following: chances to summarize the collective knowledge amassed by specialists; convenient recognizable proof of hazardous manufacturing exercises; reduction of the length of the creation process; recording potential risks of receiving inadequate or unusable items. These benefits are what drive FMEA's widespread adoption as a tool for separating essential operations from need risk.

Using exercises for robot programming, startup, testing, and shutdown as well as the key activities that go along with them—part setting, welding, and the development of external connections—this study gives a risk evaluation of the manufacture of electronic parts. Three standards are used to document and evaluate all manufacturing exercises: (1) Seriousness (S), which illustrates the influence of the consequences of disappointment on the next manufacturing exercises; (2) Event (O), which illustrates the possibility of disappointment; (3) Identification (D), which illustrates how a particular control measure may enhance the recognition of a disappointment. Finally, the three standards above are evaluated and shown, and the outcome is the gambling need number (RPN). RPN accepts values between 0 and 100. The greater the value of the need risk, the more likely it is that something will go wrong, make a mistake, or disappoint. The need risk is then recalculated after the advised exercises have been completed. Although it is assumed that the mandated movement has not caused the gamble to diminish, the subsequent value of the wager is expected to be significantly lower.

Tables keep track of all movements related to this production system. Here, a single table (Table 1) with a review of the production movement Part mounting is all that is displayed. There are four potential disappointments in this set: narrower apertures for mounting parts, wider openings, no openings, and no binding square [12]. Exercises that are recommended to reduce the risk of potential problems are also demonstrated. After using the provided methods, it may very easily be recognized that the risk of disappointment in this manufacturing movement is little and constrained.

Table 1: FMEA of the manufacturing process Mounting components

Component mounting				
Activity	The component cannot be placed			
Potential failure	Smaller diameter of the holes	Greater diameter of the holes	Missing holes	Missing square for soldering
Potential effect	Another soldering cycle	Longer soldering cycle	Another soldering cycle	Another soldering cycle
S	3	5	4	6
Potential cause	Mistake of the programmer			
0	4	4	3	3
Current controls	Visual inspection			
D	3	3	3	4
RPN	23	35	23	40
Recommended activities	Preview of the printed circuit board			
	Proper selection of components before soldering			
	Corrections of the programming code			

Person in charge and date	Engineer production			
	Engineer production			
	IT expert			
Taken activities	Preview of the printed circuit board			
	Proper selection of the components			
	Programmer' training			
S	2	2	2	2
O	3	3	3	3
D	2	3	2	2
RPN	3	5	3	3

Information related to the other basic creation activities (binding and holding) indicates that the need hazard may exceed 50 (from the most extreme 100 places). After carrying out the advised workouts, this risk can be significantly reduced.

MACHINE LEARNING

Applying a wide range of calculations and using ANNs with different designs can be used to identify machine learning.

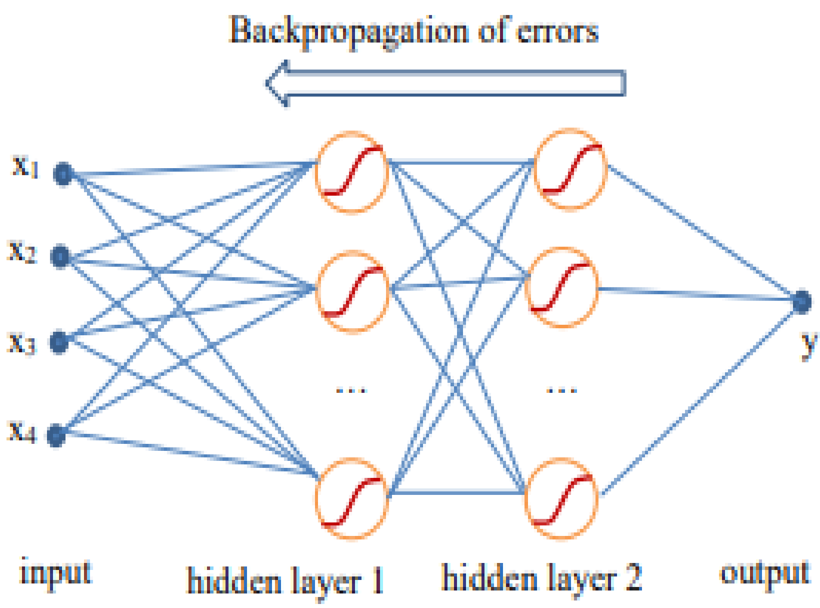

Figure 2: Back-propagation in a feed-forward artificial neural network

Figure 2 shows the development of a feed-forward artificial brain network with back-proliferation in this work. The need risk can have values of very low (PRN = 1 20), low (PRN = 21 40), medium (PRN = 41 60), high (PRN = 61 80), and extremely high (PRN = 81 100) in the ANN, which has four data sources: S, O, D, and RPN. The information sources are intended with xi, and the outcome is y. Each neuron applies a specific weight wi to the information signals it accumulates, and the result, together with the deviation b, is sent to the implementing capability AF, which may be direct or nonlinear [13]. This determines whether a straight or nonlinear relapse or grouping is carried out. Here, we have a characterisation task that needs to be completed. The outcome y then has the following structure: y = AF (x1w1 + x2w2 +... + xnwn + b).

The optimal design of an ANN is created after considering various options for the number of neurons and hidden layers with three different initiation mechanisms: tanh, rectifier, and maxout (Table 2).

Table 2: Activating procedures

Hyperbolic tangent tanh	Rectified linear unit – ReLU	maxout
tanh(x)= (ex-e-x)/ (ex+e-x)	0, x<=0 ReLU= x, x>0	maxout= max(w1 Tx+b1+ w2 Tx+b2
Range in (-1,1)	Range in [0,∞)	Range in (-∞,+∞)

The ANN with two hidden layers and 20 neurons in the first layer and 60 neurons in the second layer has the maximum precision, as shown in Table 3, with a score of 96.81%. The exaggerated digression tanh is the most sensible enacting capability for resolving this arrangement challenge.

Table 3: ANN accuracy

	Accuracy		
Hidden layers / neurons	tanh	rectifier	Maxout
2 layers /50 /50	83.03%	74.22%	98.98%
2 layers /20 /80	82.53%	82.58%	80.85%
2 layers /20 /50	83.57%	72.42%	82.58%
2 layers /20 /60	85.72%	73.54%	93.82%
2 layers /20 /20	82.02%	78.88%	98.25%

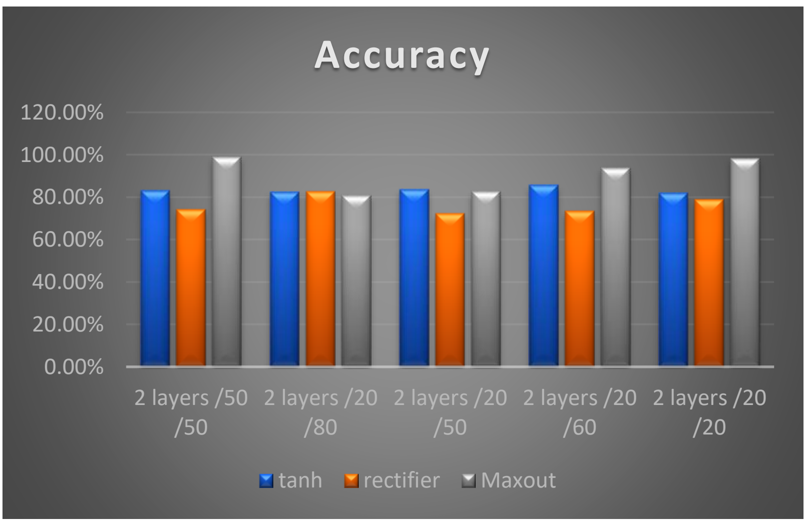

Figure 3: ANN accuracy

INSTRUMENT FOR COMPARISON THE RESULTS FROM FMEA AND MACHINE LEARNING

A promising methodology for obtaining an unbiased evaluation and forward-looking analysis of fundamental tasks in the manufacturing system for electronic parts using the robot FANUC-M10 is the correlation of FMEA data and machine learning [14]. This will help the thoughtful architects to be well-informed about any potential risks that might exist but that can be avoided if the right precautions are taken. Making a product gadget and using the suggested method could aid in navigation and prevent the occurrence of fundamental problems.

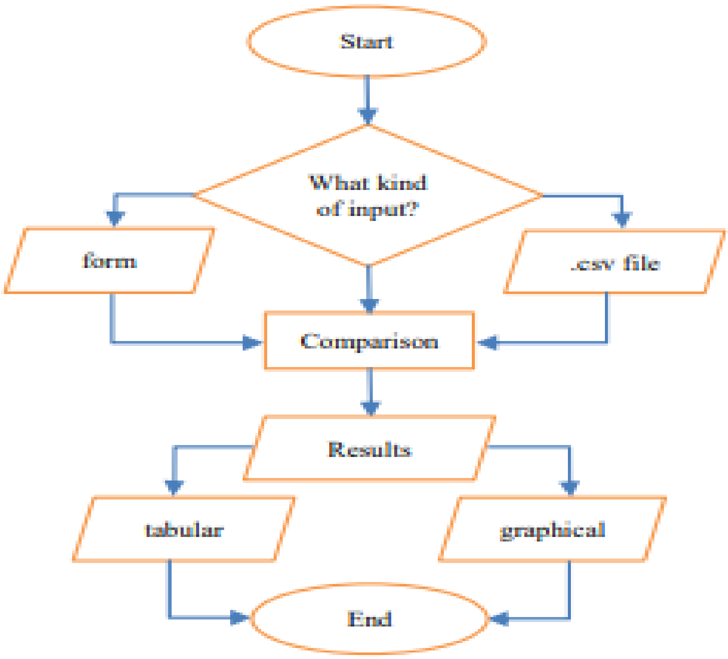

Figure 4: behind the developed software tool's algorithm

The built programming tool combines the calculation shown on Figure 4 in one place. A physical structure or a pre-structured.csv record can be used to physically insert information from FMEA and machine learning. Following an FMEA analysis, the Seriousness - S, Event - O, Recognition - D, Chance Need Number (RPNFMEA), and Hazard Need Number (RPNML) are numerical qualities that the brain organization anticipates. As the gamble is divided into five groups—extremely generally safe, okay, medium risk, high risk, and extraordinarily high risk—an assessment is also conducted.

Using two boundaries—Hazard FMEA and Chance ML—the built-in programming tool evaluates the outcomes of FMEA and Machine Learning, and the association is shown in two different ways: plainly and graphically [15]. In the straightforward and pictorial representation, in addition to the lines delineating Chance FMEA and Hazard ML, FMEA Focuses and ML Focuses are also displayed, providing true information on the frequency with which a given gamble need number is obtained.

5. Conclusion

In the modern era, specialists, mathematicians, and architects who work in the programming and exploration fields, among others, tend to be prominent and dominate the idea of artificial intelligence. Regarding the knowledge on the notion and value that artificial intelligence/machine learning can include the shop floor for the interface administrator, there appears to be a significant amount of confusion. AM can gain a lot from the use of ML and artificial intelligence. Although significant progress has been made, it will be a while before AM is refined enough to be integrated into other production processes or to become a product that consumers can buy. In the areas of cycle optimization, plan connection, plan enhancement, deformity reduction, and microstructural plan, simulated intelligence can advance AM. The ongoing techniques created for various cycles can benefit AM in many respects; nonetheless, the key hur MLe at the moment is the availability and constant quality of the data required to prepare the ML computations. The examination local area or AM producers may alter or occasionally restrict access to ebb and flow exploratory information. As a result, it is crucial to gather, store, and share accurate information while developing ML computations for AM. The perspective and various types of lead or ongoing analyses differ significantly from one another. The manufacturing region must therefore create a setting for information capability. For the information to be usable and for the ML computations to work effectively, the information age condition must also be revealed.

6. Future Scope

The applications for machine learning, especially in manufacturing, will grow quickly due to processing power, expanding information accessibility (for instance, because of low-cost sensors and the shift toward shrewd manufacturing), and quick-moving advances in the field of calculations. As of right now, administered calculations have an edge in the majority of manufacturing-related applications. However, given the swift growth of information available, improved sensor technology, and more attention, unaided tactics (including RL) may eventually become more important. Cross-breed strategies that provide "the smartest possible situation" are now in use. This is related to the recent attention given to developments in big data. In conclusion, it is highly likely that ML is already a valuable asset for various applications inside (smart) manufacturing frameworks and savvy manufacturing, and that its importance will only grow going forward. Since coordinated effort amongst numerous disciplines, such as Software engineering, Modern Designing, Science, and Electrical Designing is crucial to drive advancement, it presents both a significant open door and a critical gamble at the same time.

References

1. Galin, R.; Meshcheryakov, R.; Kamesheva, S.; Samoshina, A. Cobots and the benefits of their implementation in intelligent manufacturing. IOP Conf. Ser. Mater. Sci. Eng. 2020, 862, 032075.
2. Huang, S.; Wang, B.; Li, X.; Zheng, P.; Mourtzis, D.; Wang, L. Industry 5.0 and Society 5.0—Comparison, complementation and co-evolution. J. Manuf. Syst. 2022, 64, 424–428.

3. Lu, Y. Industry 4.0: A survey on technologies, applications and open research issues. J. Ind. Inf. Integr. 2017, 6, 1–10.
4. Johnson, R. (2020). Optimization of manufacturing processes using artificial intelligence and machine learning. Journal of Manufacturing Technology Management, 31(2), 246-265.
5. Li, X., Wang, L., & Zhang, X. (2021). A review of artificial intelligence and machine learning applications in manufacturing process optimization. Journal of Intelligent Manufacturing, 32(5), 1091-1110.
6. Zhang, Y., Chen, L., & Cao, H. (2022). Optimization of manufacturing processes through deep reinforcement learning. Computers in Industry, 132, 103704.
7. Gupta, A., Nandi, A., & Ray, A. (2023). Real-time optimization of manufacturing processes using artificial intelligence and machine learning techniques. Robotics and Computer-Integrated Manufacturing, 71, 102101.
8. Singh, V., & Saxena, A. (2023). Intelligent decision support system for optimization of manufacturing processes. International Journal of Production Research, 61(2), 477-496.
9. May, M.C.; Schmidt, S.; Kuhnle, A.; Stricker, N.; Lanza, G. Product Generation Module: Automated Production Planning for optimized workload and increased efficiency in Matrix Production Systems. Procedia CIRP 2020, 96, 45–50.
10. Mourtzis, D.; Fotia, S.; Boli, N.; Vlachou, E. Modelling and quantification of industry 4.0 manufacturing complexity based on information theory: A robotics case study. Int. J. Prod. Res. 2019, 57, 6908–6921.
11. Vukovic, M.; Mazzei, D.; Chessa, S.; Fantoni, G. Digital Twins in Industrial IoT: A survey of the state of the art and of relevant standards. In Proceedings of the 2021 IEEE International Conference on Communications Workshops (ICC Workshops), Montreal, QC, Canada, 14–23 June 2021.
12. Wuest, T.; Weimer, D.; Irgens, C.; Thoben, K.D. Machine learning in manufacturing: Advantages, challenges, and applications. Prod. Manuf. Res. 2016, 4, 23–45.
13. Kumar, S., Yadav, R., Kaushik, P., Babu, S. T., Dubey, R. K., & Subramanian, "Effective Cyber Security Using IoT to Prevent E-Threats and Hacking During Covid-19." International Journal of Electrical and Electronics Research, pp 111-116, 2022
14. S. B. G. T. Babu and C. S. Rao, "Statistical Features based Optimized Technique for Copy Move Forgery Detection," 2020 11th Int. Conf. Comput. Commun. Netw. Technol. ICCCNT 2020, 2020.
15. P. Umaeswari, S. B. G. T. Babu, G. A. Sankaru, G. N. R. Prasad, B. V. Sai Thrinath and K. Balasubramanyam, "Machine Learning Based Predicting the Assisted Living Care Needs," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 2141-2146, doi: 10.1109/IC3I56241.2022.10072955.
16. Anurag Shrivastava, Midhun Chakkaravathy, Mohd Asif Shah, A Novel Approach Using Learning Algorithm for Parkinson's Disease Detection with Handwritten Sketches', Cybernetics and Systems, Taylor & FrancisAjay Reddy Yeruva, Esraa Saleh Alomari, S. Rashmi,
17. Anurag Shrivastava, A Secure Machine Learning-Based Optimal Routing in Ad Hoc Networks for Classifying and Predicting Vulnerabilities, Cybernetics and Systems, Taylor & Francis
18. Anurag Shrivastava, SJ Suji Prasad, Ajay Reddy Yeruva, P Mani, Pooja Nagpal, Abhay Chaturvedi, IoT Based RFID Attendance Monitoring System of Students using Arduino ESP8266 & Adafruit.io on Defined Area, Cybernetics and Systems, Taylor & Francis
19. Charanjeet Singh, Syed Asif Basha, A Vinay Bhushan, Mithra Venkatesan, Abhay Chaturvedi, Anurag Shrivastava, A Secure IoT Based Wireless Sensor Network Data Aggregation and Dissemination System, Cybernetics and Systems, Taylor & Francis
20. Anurag Shrivastava, Midhun Chakkaravathy, Mohd Asif Shah, A Comprehensive Analysis

of Machine Learning Techniques in Biomedical Image Processing Using Convolutional Neural Network, 2022 5th International Conference on Contemporary Computing and Informatics (IC3I)

21. Keshav Kumar, Amanpreet Kaur, KR Ramkumar, Anurag Shrivastava, Vishal Moyal, Yogendra Kumar, A Design of Power-Efficient AES Algorithm on Artix-7 FPGA for Green Communication, 2021 International Conference on Technological Advancements and Innovations (ICTAI)
22. P William, Narendar Chinthamu, Indradeep Kumar, Manish Gupta, Anurag Shrivastava, Arun Pratap Srivastava, Schema Design with Intelligent Multi Modelling Edge Computing Techniques for Industrial Applications, 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN).
23. Kuldeep Chouhan, Abhishek Singh, Anurag Shrivastava, Structural Support Vector Machine for Speech Recognition Classification with CNN Approach, 2021 9th International Conference on Cyber and IT Service Management (CITSM).
24. A Deepak, P William, Rajat Dubey, Shilpa Sachdeva, C Vinotha, Sunny Masand, Anurag Shrivastava, Impact of Artificial Intelligence and Cyber Security as Advanced Technologies on Bitcoin Industries, International Journal of Intelligent Systems and Applications in Engineering, Vol-12, Issue-3.
25. Ajay Reddy Yeruva, Esraa Saleh Alomari, S Rashmi, Anurag Shrivastava, Routing in Ad Hoc Networks for Classifying and Predicting Vulnerabilities, Cybernetics and Systems, Taylor & Francis.
26. J. Prakash Arul Jose, Anurag Shrivastava, Prem Kumar Soni, N. Hemalatha, An Analysis of the Effects of Nanofluid-Based Serpentine Tube Cooling Enhancement in Solar Photovoltaic Cells for Green Cities, Hindawi, Journal of Nanomaterials Volume 2023,
27. Pooja Bagane, Susheel George Joseph, Abhishek Singh, Anurag Shrivastava, B Prabha, Amit Shrivastava, Classification of Malware using Deep Learning Techniques, 2021 9th International Conference on Cyber and IT Service Management (CITSM)
28. Rakesh Kumar Godi, Mule Shrishail Basvant, A Deepak, Arun Pratap Srivastava, Manoj Kumar, Akhil Sankhyan, Anurag Shrivastava, Sentiment Analysis on Omicron Tweets Using Hybrid Classifiers with Multiple Feature Extraction Techniques and Transformer Based Models, International Journal of Intelligent Systems and Applications in Engineering, Vol-12, 15-S.
29. Ayan Banik, Jarabala Ranga, Anurag Shrivastava, Subash Ranjan Kabat, AVGA MarthandS Hemavathi, Novel Energy-Efficient Hybrid Green Energy Scheme for Future Sustainability, 2021 International Conference on Technological Advancements and Innovations (ICTAI)
30. Ajay Rana, Virender Khurana, Amit Shrivastava, Durgaprasad Gangodkar, Deepika Arora, Anil Kumar Dixit, A ZEBRA Optimization Algorithm Search for Improving Localization in Wireless Sensor Network, 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)
31. Balbir Singh, Manjush Tatiya, Anurag Shrivastava, Devvret Verma, Arun Pratap Srivastava, Ajay Rana, Detection of Alzheimer's Disease Using Deep Learning, Blockchain, and IoT Cognitive Data, 2022 2nd International Conference on Technological Advancements in Computational Sciences, ICTACS