INTERNATIONAL JOURNAL FOR INNOVATIVE RESEARCH IN MULTIDISCIPLINARY FIELD ISSN: 2455-0620 Volume - 7, Issue - 12, Dec – 2021
Monthly, Peer-Reviewed, Refereed, Indexed Journal with IC Value: 86.87 Impact Factor: 6.719
Received Date: 08/12/2021 Acceptance Date: 23/12/2021 Publication Date:31/12/2021

Critical review of machine learning integration with augmented reality for discrete manufacturing

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Abstract: *This report evaluates the current state of discrete manufacturing processes, existing gaps/ challenges within such processes that may be solved through immersive technologies, and solutions through machine learning and augmented reality that may be applied to solve such gaps and challenges. Over the years, manufacturing companies have continued to evaluate ways to use immersive technologies such as machine learning and augmented reality to optimize the operations of discrete manufacturing processes, thus providing better efficiency within their operations. Currently, some mid-size and large-scale manufacturing companies have already adopted the use of machine learning and cognitive intelligence to streamline discrete operational processes in plant Floor Operations, quality Management Processes, failure Prediction, and inventory management.*

Even though such adoptions have provided optimism for optimized discrete operation processes, there is an enormous potential to evaluate more applications in streamlining the discrete operational processes of such companies. The report combines both secondary data collection processes such as the use of publications and primary data collections processes such as the use of questionnaires and interviews from professionals in the discrete manufacturing industry and those in technology to evaluate opportunities, challenges, and improvement areas in which both machine learning and augmented reality may be used for optimizing discrete manufacturing processes. Some of the challenges that ought to be solved for better implementation of machine learning and augmented reality in discrete manufacturing processes include skeptical leadership, the difference in data formats, and high maintenance costs.

Keywords: *Factory Automation, Industrial 4.0, Human Computer Interface (HCI), Digital Manufacturing, Machine learning, Augmented Reality, Industrial AR, Discrete manufacturing.*

1. BACKGROUND:

Advancements in technology, manufacturing, and engineering have made it easy to manufacture high-quality products, thus leading to an increase in available manufacturing companies. Thus, there has been increased competition among manufacturing companies which has necessitated most mid-sized and large-scale manufacturers to evaluate ion ways in which they may adopt the use of immersive technologies such as machine learning and augmented reality in optimizing their operations towards the establishment of more efficient processes to help them grow and remain competitive. Thus, such companies have used machine learning and augmented reality in optimizing basic discrete manufacturing processes such as improving plant Floor Operations, facilitating quality management processes, better prediction of failures, and facilitating inventory management. Even though such applications are beneficial, there are more chances and opportunities to use machine learning and augmented reality in optimizing more complex manufacturing operations towards better efficiency than it currently exists. Existing technological barriers and management complexities ought to be removed, including skeptical leadership, the difference in data formats, and high maintenance costs.

2. INTRODUCTION:

Machine learning is a form of artificial intelligence that enables computing systems to learn from previous experiences to make better predictions on future outcomes. Similarly, cognitive intelligence refers to generating insights and knowledge through learning from existing information or data sets. Discrete manufacturing processes may use machine learning and cognitive intelligence to help evaluate previous data and operational processes and generate insights for optimizing future operational processes. For example, data in existing manufacturing processes may help determine complexities and need to be simplified for more optimized processes. Augmented reality is an interactive-based computer experience that enables real-life enhancements of virtual objects in the physical world. When a user interacts with a virtual object, it feels like they are interacting with an object in the physical world. Mixed reality

combines elements from both the physical and virtual worlds to produce a unique feel of intuitive computer interactions. Both augmented reality and mixed reality may be used in discrete manufacturing to visualize products, operational processes and identify unsafe manufacturing conditions, thus leading to actions that optimize better discrete manufacturing processes. When both machine learning and augmented reality technologies are combined, they can optimize various manufacturing processes towards more optimized operations.

3. OBJECTIVES:

The following are the main objectives of this report.

- To evaluate the current state of discrete manufacturing processes and gaps that may be solved through technology.
- To evaluate how integrating machine learning and augmented reality may impact discrete manufacturing processes through optimizations and filling existing gaps.
- To evaluate how discrete manufacturing may utilize machine learning and augmented reality in decreasing human dependence within its operations.

4. LITERATURE REVIEW:

Previous research has been undertaken to evaluate the viability of using machine learning or augmented reality in optimizing processes and products associated with discrete manufacturing. According to Alpana & Chand, artificial intelligence will continue experiencing general operations across the manufacturing industry to help generate the necessary information for optimizing manufacturing processes [3]. Thus, companies involved in manufacturing are likely to continue evaluating how they will use machine learning to optimize their operations. Similarly, research undertaken by Lalic describes that the manufacturing industry has begun warming up on the use of augmented reality in providing better visualization on the respective products and processes involved in manufacturing such products [17].

4.1 Applications of Machine Learning and cognitive intelligence into various discrete operational processes

4.1.1 Plant Floor Operations.

Plant floor operations play a vital role in the discrete manufacturing process as most product manufacturing processes are initiated and undertaken within the plant floor. Thus, the success of any manufacturing entity in establishing optimized manufacturing processes is highly reliant on establishing optimized plant floor operations. Manufacturing companies have adopted machine learning and cognitive intelligence to help optimize plant floor operations. According to Arockiarajan, manufacturing companies produce a lot of data about the processes undertaken within the company [4]. They may be used to generate patterns/ insights that may be used to optimize the respective operations.

Machine learning is important in optimizing plant Floor operations to help predict failure and detection of suboptimal operations, thus helping determine areas within plant floor operations that may be modified towards attaining better quality products. Failure within plant floor operations may lead to delays in production processes, thus leading to loss of revenue by the company. Machine learning may use previous information and experiences on failure within plant floor operations, such as extreme changes in temperature or pressure to predict the period or points of failure within the plant floor operations. Thus, actions may be undertaken to prevent the occurrences of such failures. Suboptimal operations can delay or minimize the efficiency of existing manufacturing processes in delivering the desired value. Machine learning helps identify suboptimal operations that may be enhanced for better performance.

4.1.2 Quality Management Processes.

Manufacturing companies are continuously evaluating new ways of improving the quality of their products to keep existing customers, attract new customers and stay ahead of the competition. Conventional quality management processes are complex, thus making it challenging to determine the quality of products produced through discrete manufacturing. Companies have thus adopted machine learning to aid with undertaking quality control processes that are less complex to operate and maintain than manual-based techniques [8]. This is particularly helpful in scenarios where the desired quality requires removing the most negligible defects. In such scenarios, using manual-based quality control approaches may not identify negligible defects, thus using machine learning.

Machine learning in two ways may be used for quality management processes in discrete manufacturing. Firstly, it is used in the early detection of quality defects, mainly on the work-in-progress. Machine learning techniques such as cluster analysis and support vector machines are used to analyze data collected from the sensors and cameras that evaluate work in progress to determine even the most negligible defects, thus helping the plant operators correct the defects when the work is still in progress [30]. Thus, the final products will contain fewer defects since they were

corrected when the work was still in progress. Secondly, machine analysis enables a root cause analysis of the identified defects. Machine learning techniques such as Bayesian networks help identify the root cause for defects within the discrete manufacturing processes, thus helping eliminate them.

4.1.3. Failure Prediction.

Most discrete manufacturing companies have a predefined schedule they are supposed to follow for production to meet the demand determined by the sales and marketing department. Any failures that may occur within the machines involved within the manufacturing process may either halt or delay the plant's production activities, thus not meeting the demands established by the sales and marketing departments. Thus, there is a need for such companies to predict failure within the manufacturing processes even before they occur.

Predictive machine learning techniques may be used in predicting failures even before it occurs. Such techniques use sensors, cameras, and any other form of data input to analyze and detect anomalies such as abnormal changes in pressure or temperature that may affect the plant [13]. Thus, corrective actions may be undertaken to eliminate the anomalies and prevent failure. Similarly, the workplace for most discrete manufacturing processes contains different hazards that may risk the safety of individuals' safety within such environments. Machine learning helps identify conditions that may be hazardous, thus helping identify corrective actions that remove such hazards, thus making such a work environment safe.

4.1.4. Inventory Management.

Since it is part of their core activities, discrete manufacturing companies are required to establish effective inventory management processes. They manage different inventory forms such as raw materials, work-in-progress and finished products. When handling such inventory, it is necessary to minimize any wastage in space that may be caused due to having more inventory than needed [13]. Similarly, the right amount of inventory should always be available to meet the demand of customers or the demand of the company to undertake the relevant manufacturing processes.

Machine learning helps with inventory management in several ways. Firstly, it helps provide a smarter way to track stock. Unlike normal systems, which input data on the currently available materials and the demand for the materials to determine reorder levels, machine learning also evaluates historical data and readily available data on the market and suppliers to track inventory and determine more accurate reorder levels [10]. Secondly, machine learning reduces forecasting errors by considering data from other external sources such as news and government directives to make accurate predictions on whether specific inventory will be available at a certain time. Thus, the prediction identifies that some of the inventory will not be available in the future, thus helping the company plan to get the inventory [7].

4.2. Potential applications of using augmented reality in discrete manufacturing

Augmented reality has the potential of revolutionizing how discrete manufacturing processes are undertaken towards the establishment of better-quality products. The ability of augmented reality to use technology towards enabling the visualization of virtualized items to appear real has the potential of aiding with the visualization of manufacturing processes towards the development of high-quality products [8]. Thus, when infused with artificial intelligence, augmented reality can provide better product and insight visualizations towards more optimizing discrete manufacturing processes.

Over the last few years, more people and manufacturing companies have continued to evaluate the prospect of using digital twins to help in visualizing products developed by digital manufacturing companies (García-Peñalvo, 2021). According to Tao et al, a digital twin refers to a digital representation of any physical object, service, or process [26]. Digital twins help in providing better visualizations of physical objects, processes, and services, thus helping the designers and engineers have better insights on features or characteristics of a product, process, or service.

The operations of digital twins blend effectively with concepts related to artificial intelligence and augmented reality. Developing digital twins begins by reassigning and understanding the physical characteristics of an object through data science and applied mathematics [14]. Computational models are established to help simulate the physical object to a computerized object, thus leading to the formation of a digital twin. The physical model is then attached with sensors to record any changes that occur to it. Once the digital twin has been established, the computerized model is reconfigured. It can receive real-time input on data from the physical object, and the data is subsequently used in modifying the model to mimic the current state of the physical object [28]. Thus, machine learning helps in modelling the physical object, whereas augmented reality aids with better visualization of the model. However, augmented reality is also used in visualizing more simulations that may not be a product, such as a plant floor and warehouse operations [21].

Thus, augmented reality can be applied in discrete manufacturing in several ways. Firstly, the technology may be used for product development. According to Lalic, effective product development is a collaborative process that requires establishing different teams who will work on the product, thus making it prone to risks [17]. When such teams are working on a product, they may find it challenging to track changes or modifications made on a product. However, augmented reality may help visualize a product, the progress made in developing the product, and modifications to be made in establishing the desired product [1]. Further, augmented reality minimizes the communication among team members and their supervisors in tracking the product's progress.

Augmented reality can visualize various discrete manufacturing processes. The technology enables individuals working in discrete manufacturing companies to visualize different processes, thus enabling them to analyze different processes, identify suboptimal processes, and determine ways to optimize such processes towards more efficient product development [12]. For example, the process of developing a product from being a raw material to it becoming a finished product may be visualized to identify points within the manufacturing process that may not be optimal, thus providing better insights to the personnel involved with the manufacturing process on causes that may be leading to suboptimality, or inefficiencies [18]. Furthermore, specific environments may lead to accidents and maybe visualized to identify causes of such accidents and the respective prevention measures.

Lastly, augmented reality may be used in remote guidance or training on various discrete manufacturing processes. Augmented reality technology pr0ovides better visuals that enable a provision of remote guidance in operating certain processes. For example, when the company installs new machinery that the relevant technical personnel have not yet learned to operate, they may receive remote training and guidance on operating such machines. This helps minimize the time needed for an expert to physically go to such a plant to train the technicians on how they should use it.

Based on the information, it is clear that each of the individual technologies (Machine learning, and augmented reality) have individually contributed to streamlining discrete manufacturing processes. However, in the long run, relying on individual technologies may not effectively manage all the relevant discrete manufacturing processes. Integrating machine learning with augmented reality enables creation of more intelligent insights and visualizations on discrete manufacturing processes thus leading to more efficient and discrete manufacturing processes and operations and processes than relying on the technologies individually.

5. METHODOLOGY:

The methodology used in undertaking this research included primary and secondary data collection and analysis sources. The main secondary sources used for undertaking the research involved using online journals and publications containing information related to augmented reality and machine learning in optimizing discrete manufacturing processes. Both online publications and journals were retrieved from popular online databases such as research gate, google scholar, springer, and IJRC. For each database, a search query was initiated to retrieve articles, journals, and other publications related to machine learning and augmented reality in discrete manufacturing processes. For each search query initialized, their key terms were included, namely "augmented reality", "machine learning", and "discrete manufacturing".

Further, the search queries were limited to include materials produced from 2011 to date since any material relevant to the use of technologies such as augmented reality and machine learning in optimizing discrete manufacturing has faced more interest and research in the last decade. Based on the search query, out of more than 240 papers, articles, and business Journals, nearly 205 were excluded since they didn’t meet inclusion criteria, lacked strong evidence and didn’t have outcomes. Around 35 publications were shortlisted for integrative review. An integrative review, content analysis and Qualitative Synthesis of articles and other data sources was also undertaken to determine the information that ought to be included within this research. A questionnaire was also developed and administered to 5 engineering professionals as an online survey through google forms to gain more insights into how augmented reality and machine learning may be applied in optimizing discrete manufacturing processes.

6. SYNTHESIS AND ANALYSIS :

Upon reviewing all the data collected through the methodology, it is clear that all the materials used for this report and the individuals who provided data for the research agree that augmented reality and machine learning can optimize the operations of discrete manufacturing companies. 15% of the study material on integrated augmented reality and machine learning can significantly improve the automation of discrete manufacturing processes. Under this, the materials further identify four key areas in which augmented reality infused with machine learning can automate and optimize discrete manufacturing processes. The areas include product development, optimization of plant floor

operations, quality Management Processes, failure Prediction, and management of core operations within a discrete manufacturing plant.

Further, 16% of the materials indicate that one of the beneficiaries of process optimization through the integration of artificial intelligence and augmented reality are frontline engineers who use the technologies to gain insights that will help them make more accurate and informed decisions on various operations within the respective manufacturing plants. Frontline engineers manage various complex processes needed in helping them execute their production-related activities and processes. However, without an automated and accurate insight to help them execute their responsibilities, they are likely to take more time in making the right decision. This may be time-consuming as some decisions should be undertaken with speed. Thus, frontline engineers may make errors when trying to make uninformed decisions. However, when they use integrated augmented reality and machine learning technologies, they can gain meaningful insights and visualizations that help them make more informed decisions within less time [15].

Further, 18% of the study materials identified that integration of machine learning and augmented reality significantly support Industrial Learning and training of industrial workers on different domains related to optimization of discrete manufacturing processes. Integration of machine learning and augmented reality helps provide better visuals on various discrete manufacturing processes, products, and machinery, thus providing a more efficient mechanism to train industrial workers on the processes. Furthermore, in scenarios where new pieces of machinery are integrated and the industrial workers have not yet mastered how to operate them, augmented reality makes it possible to help remotely train the industrial workers on how to operate the system. Using augmented reality visuals can enable industrial workers to find it easy to learn about the respective operations and processes on discrete manufacturing.

Lastly, 25% of the study indicate that all the operational managers are open to adopting augmented reality technologies in helping optimize their discrete manufacturing operations. However, they are willing to adopt the technology on the conditions that any integrations limitations are eliminated and any other barriers that may make seamless adoption of the technology are removed. Currently, augmented reality is still a technology in its early stages. Thus, individuals within the manufacturing industry have yet to fully adopt it to optimize relevant operations. Thus, even though operational managers may be willing to use the technology, they need approval from other stakeholders such as the top management and the relevant investors to adopt the technology within the manufacturing facility.

7. FINDINGS & RESULTS :

Based on the analysis above, it is clear that the integration of augmented reality and machine learning can significantly improve processes involved in discrete manufacturing. Integrating augmented reality and machine learning within discrete manufacturing processes helps automate the respective operations mainly on visualizing and generating insights related to discrete manufacturing processes. Some of the discrete manufacturing processes. Some operations include generating insights and visuals related to failure prediction, quality management processes, product development, training, and remote management. As manufacturing companies aim to optimize their operations to stay ahead of the competition, they will likely strive to adopt augmented reality and machine learning integration.

Operations Managers and leaders of Discrete manufacturing companies such as Automobile, Smartphone, high tech, aerospace, machinery, electronics, etc., are interested to explore integration of Augmented reality with Machine learning. Based on the analysis undertaken on the report, for manufacturing companies to effectively adopt the application of integrated augmented reality and machine learning, they should strive to overcome the following limitations & challenges.

7.1 The transition from mobile to augmented reality interface:

To effectively enable the application of integrated augmented reality and machine learning, information technology (IT) managers ought to be convinced to work towards implementing the transition from mobile interfaces to augmented reality interfaces. In the last few years, most IT managers have adopted mobile interfaces (use of tablets and smartphones) to manage various discrete manufacturing processes. [20]. Thus, they may not have realized the full benefits that may be realized through the use of mobile interfaces.

Thus, some factory managers may resist switching to augmented reality interfaces since they may feel the need to first recover their investments on mobile interfaces before switching to AR interfaces. However, increased competition may force IT managers to quickly consider the need to switch towards augmented reality interfaces to stay ahead of the competition. Furthermore, they may also opt to implement partial inclusion of each technology, mobile and augmented reality interfaces, to benefit from both interfaces [16]. If we are able to provide better return on investments (ROI) and provide better value of AR compared to that of Mobile applications; then more discrete manufacturing operational managers and leaders may be willing to migrate to AR.

7.2. Limited buy-in from the leadership team

The leadership team from any organization is responsible for overseeing, implementing, and coordinating activities that will lead to the organization attaining its goals. In the context of discrete manufacturing, they are responsible for making the core decisions, including determining how the manufacturing processes will be undertaken to develop the end product. Thus, they also play a vital role in deciding whether the company should integrate augmented reality and machine learning technologies in managing discrete manufacturing processes [19]. Currently, there is a challenge of limited buy-in from the leadership team to integrate augmented reality and machine learning technologies in managing discrete manufacturing processes. The leadership team may consider reasons the IT managers previously indicated to resist in agreeing to implement the technology.

Thus, they may opt to first realize the benefits that arise from the current application of tablets in managing discrete manufacturing processes before proceeding to apply augmented reality interfaces to aid with the same functionalities. Furthermore, new technologies are always faced with adoption challenges where individuals may be pessimistic on whether the technology will meet the desired needs. Thus, the top management may not be sure whether integrating augmented reality and machine learning will aid the organization in optimizing its discrete manufacturing processes. This may lead to delayed adoption of the technology by the company. However, the leadership ought to be notified of the benefits of implementing the technology, including staying ahead of the competition and optimizing discrete manufacturing processes. Showcasing to the leadership team on critical differentiations that may be attained on operational efficiency through integration of Machine Learning with AR may also convince the leadership team to adopt the technology.

7.3. High Maintenance cost of Augmented reality headsets:

Augmented reality is a relatively new technology in the market. Thus, it has not yet faced major research capabilities to make it more affordable. Most available augmented reality headsets are expensive to operate, operate, and maintain. Thus, the IT managers and the leadership teams within any discrete manufacturing company may find it hard to adopt the technology to high procurement and operation costs associated with the technology. Further, the current available augmented reality headsets are not inter-operable such that they allow working with different augmented reality technologies and capabilities. Thus, when an organization procures certain augmented reality headsets, they will be limited to the number of augmented reality technologies they may adopt since they may not be integrated with such technologies [22].

In the future, this challenge is likely to gradually reduce until its fully eliminated. As more research goes into augmented reality interfaces and headsets, the technology will become cheaper and have more capabilities than its current state [23]. Further, if we are able to provide solution in which multiple business processes and multipe legacy systems can be migrated to AR, then we might give higher ROI to motivate IT Managers to procure more AR headsets This will allow organizations to adopt the technology at lower prices. Furthermore, advancements in augmented reality technologies will make it more interoperable, thus enabling organizations to adopt the use of the headsets for different technologies that may be applied to help manage discrete manufacturing processes.

7.4. Data Ingestion

The use of machine learning and augmented reality for undertaking discrete manufacturing processes is still a relatively new concept that faces data ingestion challenges. Currently, integrating augmented reality to discrete manufacturing faces data ingestion challenges whereby the data processes through machine learning are generated in a different format to that which may be ingested to augmented reality technologies. Thus, it becomes challenging for an organization to integrate the two technologies towards optimizing discrete manufacturing processes. More research needs to be undertaken towards establishing a middleware that allows the establishment of technologies that will enable data sharing between the two technologies. Thus, such research needs to involve developing a middleware that will facilitate the conversion of generated data from machine learning into data ingested to augmented reality technologies.

7.5. Network bandwidth

Both machine learning and augmented reality are technologies that require high network bandwidth capabilities to undertake their operations. Specifically, augmented reality requires high network bandwidth capabilities to enable transfer and processing of the high-resolution visuals generated by the technology. However, most companies have not yet adopted high internet and network bandwidth to effectively adopt such technologies [29]. This may hinder the ability of the company to adopt an integrated machine learning and augmented reality approach. Companies ought to first strive to update their existing network infrastructure and technologies to enable the adoption of machine learning and

augmented reality are technologies. The emergence and subsequent adoption of the fifth-generation (5G) technology will also help provide higher bandwidth capabilities within the networks of such organizations.

8. OUTCOMES:

Based on the information, it is clear that machine learning, when integrated with augmented reality, can provide discrete manufacturing companies with benefits arising out of optimizing their operational processes. The potential mainly lies in the capabilities of the individual technologies. Machine learning can use both current and historical data to generate meaningful predictions and patterns related to various discrete manufacturing processes useful in helping the relevant individuals, including frontline engineers and operational managers, optimize existing discrete manufacturing operations. Augmented reality has the potential of retrieving insights gained through machine learning and visualizing the insights for the same type of employees to have more clear and visualized insights to aid with optimizing the respective processes. The following are areas in which productivity may be enhanced by optimizing the respective operations in discrete manufacturing.

8.1. Repair and maintenance

Discrete manufacturing operations involve repairing and maintaining various machinery involved in the manufacturing process. Using integrated machine learning and augmented reality technology can enhance processes and operations related to repairing and maintaining the relevant machinery. Machine learning components can identify faulty machine parts and objects which can be visualized through augmented reality to ease the repair and maintenance process [24]. The technology can also identify parts of the machinery that may fail or need to be replaced. Augmented reality then inputs the insights to the system to help visualize the information, including ways the machine will fail, parts that are likely to cause the failure, and corrective actions that ought to be undertaken towards repairing the machine.

In some scenarios, individuals tasked with repairing and maintaining such machinery always face delay challenges since they may not have the relevant skills to identify faulty machine parts and may require experts to identify the parts. Such experts may take time before arriving at the company to solve the issue [27]. However, machine learning integrated with augmented reality may enable existing technicians visualize the parts without needing more experts thus saving the time that would have been wasted by the experts traveling to the facility to solve the issue.

8.2. Content personalization

Integration of machine learning and augmented reality may enable content personalization for the human-machine interface (HMI). Machine learning may be utilized to observe employees' behaviors, such as frontline engineers and operational managers, when undertaking plant floor operations. The same technology may then be used to analyze the predetermined roles and responsibilities of the respective employees. The technology may then be used in personalizing content and suggestions based on their activities, roles, and responsibilities. Thus, all the insights are personalized and Visualized to the employees based on their needs. This helps improve their decision-making capabilities since they are only fed with information relevant to them executing their respective activities, roles, and responsibilities [27].

8.3. Immersive Bot Agents:

Bots have continued to gain popularity due to their effectiveness in displaying the desired information to the users. Integration of machine learning and augmented reality may enable the creation of immersive bot agents [6]. Such bots will utilize machine learning to retrieve the required information and then display it to the users as augmented reality visuals, thus helping the users further grasp the information that they would inf the information would have been displayed as text [2]. Immersive bot agents may be used by factory employees such as technicians to gain quick access to real-time contextual information such as schematics, manuals, datasheets, or any other information that may interest them. The information is then presented in a visualized form, thus making it easy for them to understand the instructions that they were to follow. Further, with integration of machine learning bots to augmented reality, it is possible to provide engineers with the capability of using voice commands with the bots. The bots would then analyze the voice commands and intelligently fetch the instructions which may include manuals, schematics, and data sheets thus simplifying the work of the engineers.

8.4. Industrial Training.

Training employees is critical in ensuring that employees can fully execute emerging discrete manufacturing processes and technologies. However, training employees to update their skills may be time-consuming since they spend time undertaking various training sessions [20]. Thus, during the training period, the organization may miss the

opportunity to gain value from the skills in which the employees may be seeking training. A combination of machine learning and augmented reality may develop simulations that may help employees harness their industrial skills. Machine learning and augmented reality may help create a simulated environment for employees to train on different task procedures and engineering operations [4]. This helps reduce the communications initiated by employees to clarify various task procedures assigned to them. Conventional training methods may be difficult for employees to understand. However, using augmented reality may provide more clear visuals to the employee, thus making it easy for them to understand various industrial training concepts [11]. Furthermore, the simulations provide the employees with an environment to test the practicality of whatever they are learning without fearing an error since the tests are done in a simulated environment. Thus, industrial training undertaken through machine learning and augmented reality provides more effective industrial training on discrete manufacturing.

9. CONCLUSION:

Based on the information provided, it is clear that integrating augmented reality and machine learning can significantly optimize discrete manufacturing processes. In an era where manufacturing companies continue to face increased competition due to advancements in technology and manufacturing processes, they need to evaluate the use of integrated augmented reality and machine learning processes to improve discrete manufacturing operations towards better manufacturing processes. Previously, machine learning has been utilized in plant floor operations, quality Management Processes, failure Prediction, and inventory management. Similarly, augmented reality has been used for visualizing products, machinery, and processes. Integrating the two technologies can aid organizations to undertake discrete manufacturing processes such as optimizing repair and maintenance, discrete manufacturing content personalization, development of immersive Bot Agents for discrete manufacturing, and Industrial Training.

REFERENCES:

1. Advances in production management systems: Artificial intelligence for sustainable and resilient production systems: IFIP WG 5. 7 International Conference, APMS 2021, Nantes, France, September 5-9, 2021, proceedings. (2021). Springer Nature.
2. Ahn, S. J., & Fox, J. (2017). Immersive virtual environments, avatars, and agents for health. Oxford Research Encyclopedia of Communication. https://doi.org/10.1093/acrefore/9780190228613.013.325
3. Alpana, & Chand, S. (2020). Discovery of smart technology in manufacturing industries: Automated characterization of coal using machine learning. 2020 International Conference on Smart Electronics and Communication (ICOSEC). https://doi.org/10.1109/icosec49089.2020.9215419
4. Amza, C. G., Zapciu, A., & Teodorescu, O. (2018). Augmented reality application for industrial non-destructive inspection training. AIP Conference Proceedings. https://doi.org/10.1063/1.5024152
5. Arockiarajan, A. (2020). Advances in industrial automation and smart manufacturing: Select proceedings of ICAIASM 2019. Springer Nature.
6. Bonsch, A., Hoffmann, J., Wendt, J., & Kuhlen, T. W. (2019). Evaluation of omnipresent virtual agents embedded as temporarily required assistants in immersive environments. 2019 IEEE Virtual Humans and Crowds for Immersive Environments (VHCIE). https://doi.org/10.1109/vhcie.2019.8714726
7. Carou, D. (2021). Aerospace and digitalization: A transformation through key industry 4.0 technologies. Springer Nature.
8. Chu, C., Wang, L., Liu, S., Zhang, Y., & Menozzi, M. (2021). Augmented reality in smart manufacturing: Enabling collaboration between humans and artificial intelligence. Journal of Manufacturing Systems, 61, 658-659. https://doi.org/10.1016/j.jmsy.2021.05.006
9. Da Silveira Dib, M. A., Ribeiro, B., & Prates, P. (2021). Federated learning as a privacy-providing machine learning for defect predictions in smart manufacturing. Smart and Sustainable Manufacturing Systems, 5(1), 20200029. https://doi.org/10.1520/ssms20200029
10. García-Peñalvo, F. (2021). Information technology trends for a global and interdisciplinary research community. IGI Global.
11. Gattullo, M., Laviola, E., Fiorentino, M., & Uva, A. E. (2021). Positive computing in virtual reality industrial training. 2021 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct). https://doi.org/10.1109/ismar-adjunct54149.2021.00083
12. Grunow, O. (2016). Smart factory and industry 4.0. The current state of application technologies: Developing a technology roadmap. GRIN Verlag.
13. Helo, P., & Hao, Y. (2021). undefined. Production Planning & Control, 1-18. https://doi.org/10.1080/09537287.2021.1882690

14. Ivaschenko, A., Khorina, A., & Sitnikov, P. (2018). Accented visualization by augmented reality for smart manufacturing aplications. 2018 IEEE Industrial Cyber-Physical Systems (ICPS). https://doi.org/10.1109/icphys.2018.8390759
15. Kim, M., Jeong, J., & Bae, S. (2019). Demand forecasting based on machine learning for mass customization in smart manufacturing. Proceedings of the 2019 International Conference on Data Mining and Machine Learning. https://doi.org/10.1145/3335656.3335658
16. Kotsiopoulos, T., Sarigiannidis, P., Ioannidis, D., & Tzovaras, D. (2021). Machine learning and deep learning in smart manufacturing: The smart grid paradigm. Computer Science Review, 40, 100341. https://doi.org/10.1016/j.cosrev.2020.100341
17. Lalic, B., Majstorovic, V., Marjanovic, U., Cieminski, G. V., & Romero, D. (2020). Advances in production management systems. Towards smart and digital manufacturing: IFIP WG 5.7 International Conference, APMS 2020, Novi Sad, Serbia, August 30 – September 3, 2020, proceedings, part II. Springer Nature.
18. Lampropoulos, G., Keramopoulos, E., & Diamantaras, K. (2020). Enhancing the functionality of augmented reality using deep learning, Semantic Web and knowledge graphs: A review. Visual Informatics, 4(1), 32-42. https://doi.org/10.1016/j.visinf.2020.01.001
19. Lorenz, M., Knopp, S., Kim, J., & Klimant, P. (2020). Industrial augmented reality: 3D-Content editor for augmented reality maintenance worker support system. 2020 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct). https://doi.org/10.1109/ismar-adjunct51615.2020.00060
20. Loureiro, S. (2020). Managerial challenges and social impacts of virtual and augmented reality. IGI Global.
21. Matuszka, T. (2013). Augmented reality supported by Semantic Web technologies. The Semantic Web: Semantics and Big Data, 682-686. https://doi.org/10.1007/978-3-642-38288-8_51
22. Paolis, L. T., & Bourdot, P. (2020). Augmented reality, virtual reality, and computer graphics: 7th International Conference, AVR 2020, Lecce, Italy, September 7–10, 2020, proceedings, part II. Springer Nature.
23. Preez, A. D., & Oosthuizen, G. A. (2019). Machine learning in cutting processes as enabler for smart sustainable manufacturing. Procedia Manufacturing, 33, 810-817. https://doi.org/10.1016/j.promfg.2019.04.102
24. Sharp, M., Ak, R., & Hedberg, T. (2018). A survey of the advancing use and development of machine learning in smart manufacturing. Journal of Manufacturing Systems, 48, 170-179. https://doi.org/10.1016/j.jmsy.2018.02.004
25. Sibalija, T., & Davim, J. P. (2021). Soft computing in smart manufacturing: Solutions toward industry 5.0. Walter de Gruyter GmbH & Co KG.
26. Tao, F., Zhang, M., & Nee, A. (2019). Digital twin and virtual reality and augmented reality/Mixed reality. Digital Twin Driven Smart Manufacturing, 219-241. https://doi.org/10.1016/b978-0-12-817630-6.00011-4
27. Vijayalakshmi, C., & Pakkir Mohideen, S. (2021). Personalization of data using machine learning. Materials Today: Proceedings. https://doi.org/10.1016/j.matpr.2020.11.321
28. Wilkins, N. (2019). Internet of things: What you need to know about IoT, big data, predictive analytics, artificial intelligence, machine learning, cybersecurity, business intelligence, augmented reality and our future.
29. Wu, Z., & Christofides, P. D. (2020). Smart manufacturing: Machine learning-based economic MPC and preventive maintenance. Smart Manufacturing, 477-497. https://doi.org/10.1016/b978-0-12-820028-5.00014-x
30. Zhang, Y., & Kwok, T. (2018). Design and interaction interface using augmented reality for smart manufacturing. Procedia Manufacturing, 26, 1278-1286. https://doi.org/10.1016/j.promfg.2018.07.140

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