International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 10 Issue: 03 | Mar 2023 www.irjet.net p-ISSN: 2395-0072

Advancing Digital Twin through the Integration of new AI Algorithms

Usman Ibrahim Musa[1], Sukanta Ghosh[2]

[1,2] School of Computer Applications, Lovely Professional University, Punjab, India.

Abstract - *This research paper explores the integration of AI algorithms to advance the technology of digital twins. Digital twin is a virtual representation of a physical object, process, or system that enables real-time monitoring and analysis, which has the potential to transform various industries. However, despite its potential, the technology faces several challenges, such as data management, scalability, and accuracy. This paper proposes the use of AI algorithms to address these challenges and improve the performance of digital twin technology. The proposed AI algorithms can help overcome the challenges faced by digital twin technology, making it more scalable, accurate, and efficient. This paper provides a valuable contribution to the field of digital twin technology and offers insights into its potential applications and challenges.*

Key Words: Digital Twin, AI, Algorithms.

1. INTRODUCTION

This research focuses on the topic named "Digital Twin". Digital-Twin is simply a virtual representation of a physical system or object that allows for simulation and analysis of real world scenarios [1] [2] [3]. According to the definition of the Digital Twin given by a researcher; Digital twin can be defined as a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making [1].

Nowadays, the use of this Digital-Twin is popular in many industries such as manufacturing, aerospace, and healthcare. And it has also led to important improvements in quality, efficiency, and cost-effectiveness in such industries [1] [2]. A peer-reviewed research recently published on smart manufacturing and where it reviews the recent development of Digital Twin technologies in manufacturing systems, and research issues of Digital Twin-driven smart manufacturing in the context of Industry 4.0. [2]. In light of the foregoing, one of the most significant challenges is the integration of new AI algorithms to advance the Digital Twin. The AI algorithms we are talking about work and enable machines to learn and make decisions based on the given data which has played a role to the development and integration of smart systems that can predict and respond to real-world challenges [3]. With that being said, the integration of AI algorithms into digital twins in this research has the potential to enhance their capabilities, making them more accurate and effective.

Fig.1 Few of Digital Twin's Applications

There are several applications of the Digital Twin which include Manufacturing, Healthcare, and Aerospace as mentioned earlier, the proposed AI algorithms that will be of great help in enhancing the Digital Twins in these industries are available further in this research. The purpose of this research paper is to explore the advancements in digital twins through the integration of new AI algorithms. The paper will examine the current state of digital twins, the challenges faced in their development, and the potential benefits of integrating new AI algorithms. The paper will also explore the types of AI algorithms that can be integrated into digital twins and their applications.

We will begin by discussing the definition of digital twins and their current state in this research. Furthermore, the paper will also provide an overview of the different types of digital twins and their applications in various industries, and it will then explore the challenges faced in the development of digital twins, such as the need for accurate data and the complexity of the models and how to overcome them with the help of the new algorithms. The paper will also discuss the potential benefits of the digital twin. We have collected some research questions on this topic to make it more readable and accurate, these research questions are further explained in the next section. A photo by Data Center Knowledge is presented below on the concept of the Digital Twin.

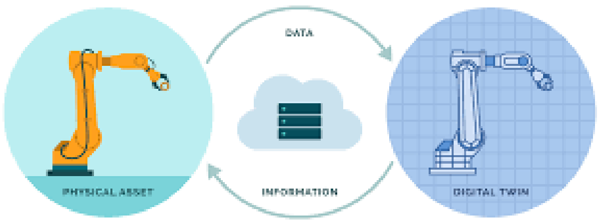

Fig. 2. Digital Twin Concept.

Research Questions

1. What is Digital Twin and how it works?
2. What is the relationship between AI and Digital Twin and the benefits of combining the two?
3. What are the possible tools for creating AI-enabled Digital Twins?
4. What are the current challenges in Digital Twin Technology and how can AI be used to address those challenges?
5. What is the research gap existing in the integration of AI and Digital Twin technology?

1. What is Digital Twin and how it works?

As defined by most of the researchers, Digital-Twin refers to a virtual representation of a physical object that allows for simulation and analysis of real-world scenarios [1] [2]. On the other hand, a Digital twin can be defined as a virtual representation of a physical asset enabled through data and simulators for real-time optimization, prediction, monitoring, and controlling [2] [3].

This section of this study will explain how the digital twin work in a basic way that will be easy to understand. First and foremost, imagine you have an identical twin brother or sister which you look alike, you have the same DNA, and you were born at the same time. However, you are two separate individuals with your own experiences and expertise. In this case, a digital twin is kind of like your twin, but for a physical object or system. Let's assume you have a car, a digital twin of your car is a virtual model that's created using computer software where it looks and behaves like your car, but it exists entirely in the digital world [4]. That digital twin of your car can be used to monitor and analyse how your car is performing. There will be sensors attached to your car that can collect data on several things like its fuel consumption, speed, and engine temperature and the data can be fed into the digital twin, which can then simulate how your car is functioning in real-time [4] [5]. This is very useful because it allows you to identify potential problems before they become serious, one example is, if the digital twin shows that the engine is running too hot, you can take your car in for maintenance before it breaks down on the side of the road.

The Digital Twin on the other hand, is a term that distinguishes itself from the digital model and digital shadow. Despite being a key enabler for digital transformation in manufacturing, there is no common understanding of the term DT in literature, and literature on the highest development stage. However, the digital twin is a key building block for smart factory and manufacturing under the Industry 4.0 paradigm [7]. It is a digital model for emulating or reproducing the functions or actions of a real manufacturing system [8]. DT is created during the design stage of a complex manufacturing system and is usable throughout its lifecycle [7]. Its seven basic elements include controller, executor, processor, buffer, flowing entity, virtual service node, and logistics path of a DMS for formally representing a manufacturing system and creating its virtual model. A digital twin represents an organic whole of physical assets and their digitized representation that mutually communicate and co-evolve through bidirectional interactions. The entities, behaviours, and relations in the physical world are digitized holistically to create high-fidelity virtual models. Virtual models depend on real-world data from the physical world to formulate their real-time parameters, boundary conditions, and dynamics. DT has emerged over the past decade in the domains of manufacturing, production, and operations [8]. It facilitates learning through modelling, simulation, and analysis and has been used in the PDCA cycle for production management including design, operation, and improvement of production systems [8]. Monitored data from physical artefacts to digital processes is an essential component of DT which generates new knowledge. Additionally, well-defined services can be supported by DT such as monitoring, maintenance, management, optimization, and safety [7] [8]. DT is attracting attention from both academia and industry and has been classified as one of the top 10 technological trends with strategic values for three years from 2017 to 2019 by Gartner. Lockheed Martin listed DT as one of the six game-changing technologies for the defence industry. Digital twins are also used in manufacturing and engineering. A digital twin of a factory or a bridge can be used to simulate different scenarios and test how the system will behave under different conditions [5]. This can help engineers identify potential design flaws and optimize the performance.

2. What is the relationship between AI and Digital Twin and the benefits of combining the two?

The integration of artificial intelligence (AI) into Digital Twins can greatly enhance their capabilities and expand their beneficial applications. AI can open up entirely new areas of application for Digital Twins, including cross-phase industrial transfer learning [9]. One way in which AI enhances the capabilities of Digital Twins is through transfer learning [10]. Transfer learning involves transferring knowledge from one lifecycle phase to another to reduce the amount of data or time needed to train a machine learning algorithm. With AI, Digital Twins can use real-time data to forecast the future of physical counterparts, thus significantly improving predictive maintenance and reducing downtime [10]. Furthermore, AI facilitates the development of new models and technology systems in the domain of intelligent manufacturing, particularly in cross-phase industrial transfer learning use cases [10][9]. The implementation of AI in Digital Twins allows for optimization, adaptation, and reconfiguration of industrial automation systems, which can lead to significant improvements in efficiency and cost savings [11]. Moreover, the intelligent Digital Twin architecture can be a possible implementation of AI-enhanced industrial automation systems, providing the four fundamental sub-processes of intelligence - observation, analysis, reasoning, and action [11]. To achieve this, an artificial intelligence component is connected with the industrial automation system's control unit and other entities through a series of standardized interfaces for data and information exchange [10] [11]. With the integration of AI into Digital Twins, algorithms can be fine-tuned once real data becomes available, significantly speeding up commissioning and reducing the probability of costly modifications [9]. Overall, equipping Digital Twins with AI functionalities can greatly expand their scope and usefulness for industrial automation systems.

The combination of AI and Digital Twin technology can lead to new and innovative solutions for disaster response and emergency management. AI can enable the collection and analysis of situational data from multiple sources in near real-time, including remote sensing, social sensing, and crowdsourcing technologies. This can enhance data collection, analysis, and decision-making in disaster situations and humanitarian crises [12]. Moreover, integrating heterogeneous data using AI can provide critical insights needed by responders and relief actors [12]. The proposed Disaster City Digital Twin vision offers significant contributions and implications for research and practice of AI and city management in disasters, promoting interdisciplinary convergence in the field of ICT for disaster response and emergency management [12] [13]. This integration can also introduce autonomy for in-situ self-maintenance and autonomous repair capability [13]. By combining AI and Digital Twin technology, it is possible to enhance the performance of disaster response and emergency management, providing valuable information that can inform future research [12].

3. What are the possible tools for creating AI-enabled Digital Twins?

There is no one technology that can be used to execute digital twin; rather, various technologies, including AI, IoT, and communication technologies, are combined. Each technological component may be implemented using a wide range of techniques. Only tools that support component integration, AI, and machine learning are included in this section. **Table 1** summarizes a few of the commonly used AI technologies that may give assistance at various phases of digital twinning.

Table 1. Few tools for creating AI-enabled Digital Twins

References	Type of the Tool	Name of the Tool	Owner of the Tool
[19]	API	Gym	OpenAI
[6]	AI Tool	Matlab	Mathworks
[14]	AI Tool	Tensorflow	Google
[17]	API	Keras	Francois
[20]	AI Tool	Rliab	OpenAI / UC Barkeley
[16]	AI Tool	Caffe	Barkeley AI Research (BAIR)
[15]	AI Tool	CNTK	Microsoft
[18]	AI Tool	Weka	University of Waikato

4. What are the current challenges in Digital Twin Technology and how can AI be used to address those Challenges?

Digital twin technology is an emergent field that has seen recent growth and attention in case studies. Despite its potential, digital twin technology faces significant challenges in its growth and implementation, which must be addressed for it to be successfully integrated into various domains. The challenges associated with digital twin technology are significant and include a lack of predictive ability, the infancy of digital twins, complexity and scale of cyber-physical systems, and the need for manual construction of digital systems and definition of system components [21]. Nevertheless, digital twin technology offers the ability to provide deep insights into the inner workings of any system, including the interaction between different parts of the system and the future behavior of their physical counterpart in a way that is actionable for their users and stakeholders [22]. The development of industrial software solutions to virtual commissioning has greatly improved the accuracy and user-friendliness of off-line programming robotic systems and verifying control logic [21 [22]. In addition, there is an increasing trend toward the widespread implementation of digital twin technology in several domains, such as industrial, automotive, medicine, smart cities, etc. [22]. To overcome the challenges associated with digital twin technology and facilitate its implementation, it is important to have a comprehensive understanding of the technology challenges, limitations, and trends as well as a domain-specific revision of applications. Therefore, a systematic literature review aims to present such a view on the digital twin technology and its implementation challenges and limits in various domains [22]. For instance, research toward the development of a metal additive manufacturing (AM) digital twin can be organized logically into a hierarchy of four levels of increasing complexity, which requires deep integration of key enabling technologies such as surrogate modeling, in-situ sensing, hardware control systems, and intelligent control policies. Ultimately, digital twins are considered a shift away from costly physical testing and can provide a new perspective into cyber-physical system testing due to the coupling between digital and physical worlds [22] [21].

Artificial Intelligence (AI) is a promising approach to address the challenges in Digital Twin technology. AI-enhanced interaction in DTS is presented in detail in the paper, and it is shown that predictive control through AI-enhanced DTS improves real-time interaction [23]. AI is also an effective approach to improve the intelligence of the physical shop-floor, and can be used to create virtual counterparts of robot manufacturing systems through digital twin simulation and communication technologies [23][21]. The intelligent scheduler for work cell scheduling can be safely trained on these virtual systems using Deep Reinforcement Learning (DRL) algorithms, which can incorporate AI in the industrial control process. The use of AI in digital twin technology can provide modern solutions to the growing needs of digitalization in manufacturing [21]. System-level digital twinning can be expanded to complex manufacturing systems with deep neural networks to overcome the challenges in Digital Twin technology. Virtual commissioning using large-scale simulations, prompt system indicators, and computation technologies can establish a life-like digital manufacturing platform [21]. Moreover, a data-driven approach that utilizes digital transformation methods can automate smart manufacturing systems, while integrating a smart agent into industrial platforms can expand the usage of the system-level. Virtual commissioning can accelerate the training, testing, and validation of smart control systems, providing a step towards system-level digital twinning. Furthermore, AI-driven robotic manufacturing cells can be developed through the ideation of a platform optimization tool as a concept of digital engineering [21] [23]. Therefore, AI can play a significant role in overcoming the challenges in Digital Twin technology and revolutionize manufacturing processes.

5. What is the research gap existing in the integration of AI and Digital Twin technology?

Digital Twin technology has recently been proposed and finds broad applications in industries such as the manufacturing, healthcare and aerospace. The combination of wireless communications, artificial intelligence (AI), and cloud computing provides a novel framework for futuristic mobile agent systems. The digital twin builds a mirror integrated multi-physics of the physical system in the digital space [24]. However, the communication framework for DT has not been clearly defined and discussed. The article describes the basic DT communication models and presents open research issues [24]. The proposed Digital Twin paradigm includes four components: multi-data sensing for data collection, data integration and analytics, multi-actor game-theoretic decision-making, and dynamic network analysis [25]. AI-enabled remote sensing, social sensing, and crowdsourcing technologies are important elements of the Digital Twin for near-real-time gathering and analysis of disaster and crisis situations [25]. The advances in AI have brought opportunities to gather, store, and analyze various types of data related to a disaster city, and integrating ICT and AI techniques into a digital twin paradigm is possible for Disaster City Digital Twin [24] [25]. Edge computing technology is introduced to build an intelligent traffic perception system based on edge computing combined with digital twins. Some technological solutions for monitoring construction work have recently become available and applied commercially [26].

2. METHODOLOGY

All of the methodologies utilized in this research will be presented in full in this section, along with appropriate analyses and graphics. We gathered the algorithms from many sources, and all of the stages and approaches will be detailed in this part.

i. Data Sources: This paper's literature is made up of multiple research publications and articles from various sources. Figure 3 depicts a visual or graphical illustration of the data sources used in this study, as well as their corresponding percentages. In addition, as shown in **Table 2**, we created a table of the databases and their corresponding URLs that were all employed in this research.

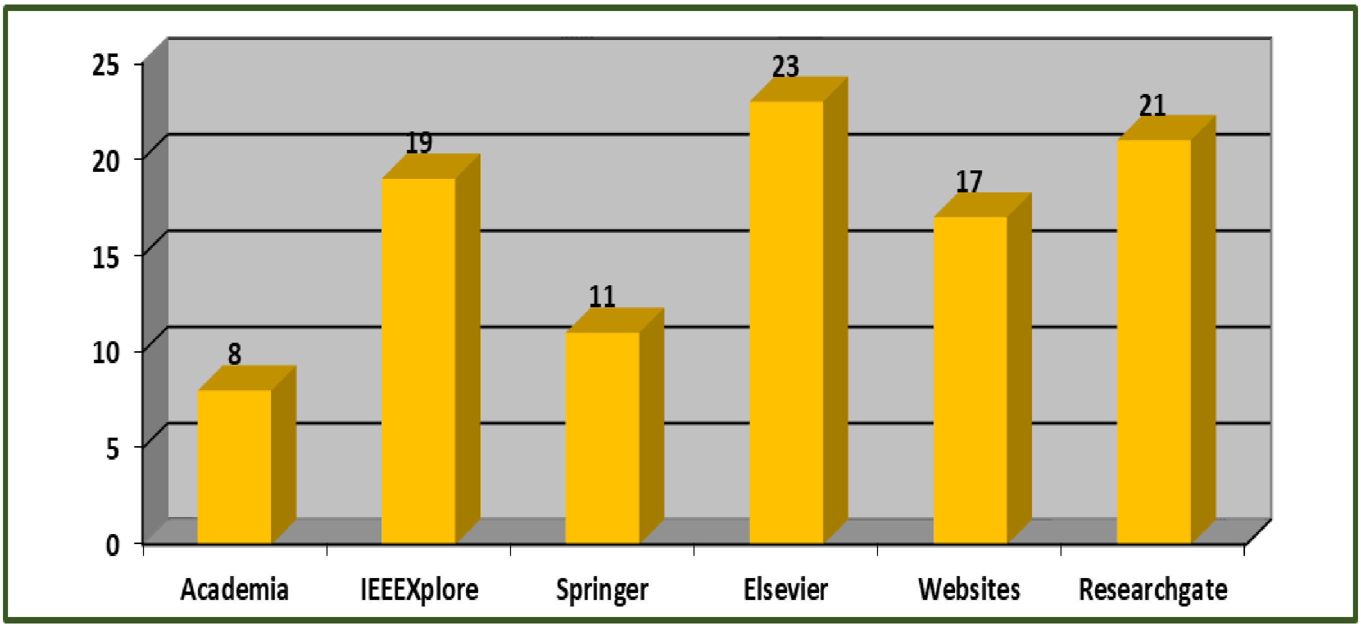

Fig. 3. Graphical Representation of the Data Sources

Table 2. Sources and their Respective URLs

Sources	**URLs**
Researchgate	https://www.researchgate.net/
IEEEXplore	https://www.ieeexplore.ieee.org/
Elsevier	https://www.elsevier.com/
Academia	https://www.academia.edu/
Springer	https://www.springer.com/

ii. Exploration Criteria: It is evident that this research necessitates a thorough examination of earlier sources from both the digital twin and artificial intelligence domains; so, we gathered all references and calculated the proportion of articles utilized in this research for each and every year. **Figure 5** depicts a graphical depiction of the same, with all percentages clearly indicated. Despite the fact that certain papers were represented as "others," which signifies they are ancient papers and make up less than 1% of the paper. For example, the majority of the publication's date from 2015 to 2023, with one paper each from 1999, 2003, and 1988. These papers are collectively referred to as "others."

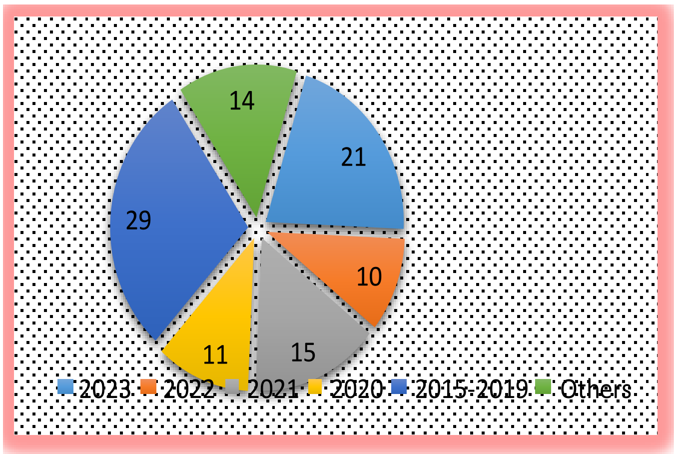

Fig. 4. Papers used from previous years.

AI Developments in Digital Twin for Industries

As discussed previously right in the introduction part of this paper, digital twin has a wide range of application such as manufacturing, healthcare etc. Additionally, the AI has been very useful to these areas where digital twin works, the AI enhanced the working of the digital twin in those areas efficiently and effectively. This section will discuss thoroughly on the AI developments in the digital twin for various industries as follows;

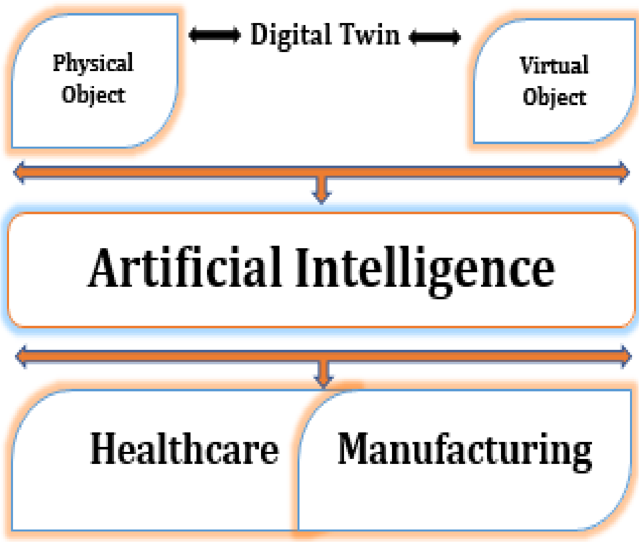

Fig. 5. AI Developments in Digital Twin Industries

i. Digital twin technology has been gaining attention in the manufacturing industry as it offers a powerful way to optimize processes and improve efficiency [25]. The integration of AI in digital twin technology has further enhanced its capabilities, allowing it to learn from past data and make predictions for the future. As stated by the paper [11], that healthcare industry is another area where digital twin technology, combined with AI, has the potential to improve patient outcomes significantly. Digital twins can be created for individual patients, which can help doctors tailor treatments and medication plans to suit each patient's unique needs. **Table 3** shows the same.

ii. As a result of extensive research conducted in this research for digital twin in healthcare industries, we have compiled a comprehensive list of several AI developments that have been implemented by various researchers. In order to provide a clear and concise overview of these advancements, we have prepared **Table 4**, which presents a detailed analysis of the various applications of AI, digital twin use cases, the AI approach utilized for each, and corresponding references for further exploration. This compilation serves as a valuable resource for individuals and organizations seeking to enhance their knowledge and understanding of the latest developments in digital twin technology.

Table 3. AI Developments in Digital Twin for Manufacturing

References	Applications and Digital Twin Use-Cases	AI Approach
[27]	Development fault diagnosis is the application and the digital twin use case is shop floor	Deep neural networks with transfer learning.
[33]	Used for quality improvement for product assembly and the digital twin use case is for remote laser welding.	Convolutional Neural Networks (CNN)
[34]	For Forecast work-in-process time, the digital twin use case is shop floor.	Multiple linear regression models
[35]	Used for multi life cycle process forecast and AGV fault diagnosis, the digital twin use case is Automated guided vehicles (AGVs)	The AI approach used was Deep Learning
[36]	For product quality, the digital twin use case was CNC bending machine.	The Artificial Neural Networks (ANNs)
[37]	The application was for collaborative data management and AM defect analysis, the use case for digital twin is project MANUELA.	Deep Learning
[28]	Job scheduling optimization and optimal resource allocation. The use case is shop floor of aircraft engine.	Genetic algorithm and evolution algorithm
[29]	Resource management and product quality control, digital twin use case is satellite assembly shop floor.	Genetic algorithm and PSO
[30]	Product design and process optimization. For shop floor.	Machine Learning and Deep Learning
[38]	Performance optimization for dew-point cooler	Multi-object evolutionary optimization and feed-forward neural network

[31]	Process planning and optimization, the digital twin use case is for marine diesel engine	Mathematical and Statistics Big Data Analytics
[32]	Process control and scheduling optimization for robots manufacturing cell.	Deep Reinforcement Learning
[39]	Robot Optimization for avoiding obstacles.	Ant colony optimization

Table 4. AI Developments in Digital Twin for Healthcare

References	Applications and Digital Twin Use-Cases	AI Approach
[48]	Application was crack state estimation and fatigue life prediction for aircraft.	Probabilistic Models
[49]	The application was for Damage Detection, the didgital twin use case if Bottom-set gillinet	Artificial Neural Networks (ANNs)
[50]	Plasma radiation detection. The digital twin use case was a bolometer.	Fuzzy logic
[40]	Degradation of winding insulation and short circuits for faults in motor. Digital twin use case was for Electric Vehicle Motor.	Fuzzy Logic and Artificial Neural Networks (ANNs)
[51]	Expert fault diagnosis for aircraft engine	Artificial Neural Networks (ANNs)
[54]	Ship speed loss- prediction due to marine fouling. Used for ship.	Deep Learning
[53]	Fault diagnosis for photovoltaic energy conversion	Used the holistic fault diagnosis approach
[44]	Gearbox prognosis and fault detection for wind turbine	Neural Networks
[45]	The application was capacity fade and power fade for the battery's aging level prediction, the digital twin use case was lithium and lead-acid battery system.	The approach used was particle swarm optimization
[46]	Cutting tool fault and life prediction with digital twin use case of CNC machine tool (CNCMT)	Bayesian model and regression model.
[41]	The application was fault prediction and maintenance in shaft bearing, the use case was an aero engine	Neural Network and Deep Learning
[42]	Spacecraft structural life prediction for spacecraft.	Dynamic Bayesian Network was used
[43]	Fault prediction and optimization, the digital twin use case was CNC machine Tool (CNCMT)	Machine Learning
[47]	Track asset degradation and faults detection. The digital twin use case was the gearbox, rotating shaft bearing, and aircraft turbofan engines	Generative Adversarial Networks (GANs)
[52]	Dynamically detect structural damage or degradation and adopt strategy. Used for UAV.	Static-condensation reduced-basis-element method, and Bayesian state estimation

This section above explains a few AI advances in the health industries created by various researchers. **Table 4.** Displays the numerous applications, digital twin use cases, the AI technique for the same, and the relevant references for each.

3. PROPOSED AI ALGORITHMS

In this section, we present to you a comprehensive overview of the latest AI algorithms that could greatly enhance Digital Twin technologies. In today's digital era, the use of AI algorithms is becoming increasingly common as they have the potential to vastly improve the accuracy and efficiency of digital twin technologies. We have compiled a list of some of the most recent and innovative AI algorithms being used today, and we have summarized their applications and key features in **Table 5** below. Our goal is to provide you with useful insights into the latest advancements in digital twin technologies, and to show you how these technologies are transforming various industries.

It is important to stay up-to-date with the latest trends and technologies, especially in a world that is constantly changing and evolving. That is why we believe that this information could prove to be immensely valuable. By providing an in-depth understanding of the latest AI algorithms being used in digital twin technologies, we hope to empower the reader to make informed decisions and take advantage of the opportunities that arise. And is these AI algorithms continue to evolve, we believe that they will revolutionize the way industries operate. The impact of digital twin technologies is already being felt across various industries, from healthcare to manufacturing to transportation. With the help of AI algorithms, these technologies will continue to improve, leading to greater efficiency, accuracy, and productivity.

Table 5. Proposed AI Algorithms that could Improve Digital Twin

Algorithm	Features	Description	Impact to Digital Twin
Generative Adversarial Networks (GANs)	Synthetic Data Generation, Data Augmentation	GANs are a type of neural network that can generate new data samples that are similar to the ones in the training data. They can be used to train Digital Twin or to generate synthetic data for testing and validation	Improves training and validation of Digital Twins through synthetic data generation and augmentation
Recurrent Neural Networks (RNNs)	Sequential data processing, time-dependent data	RNNs are a type of neural network that can process sequential data, such as time series data or natural language text. They can be used to improve the accuracy of Digital Twins that involve time-dependent data, such as simulations of weather patterns or financial market trends.	Improves accuracy of Digital Twins that involve time-dependent data by enabling better sequential data processing and analysis.
Reinforcement Learning	Learning through interactions, prediction improvement	Reinforcement Learning is a type of machine learning algorithm that enables agents to learn through interactions with their environment. It can be used to improve the accuracy of Digital Twins by training the model to make better predictions based on the data available.	Improves accuracy of Digital Twins by enabling better prediction through learning from interactions with the environment.
Bayesian Networks	Probabilistic graphical model, complex relationship representation	Bayesian Networks are a type of probabilistic graphical model that can represent complex relationships between variables. They can be used to improve the accuracy of Digital Twins by enabling them to model complex systems with multiple interacting variables.	Improves accuracy of Digital Twins by enabling better representation and modeling of complex systems with multiple interacting variables.
Deep Learning	Neural network with multiple layers, data analysis, learning	Deep Learning is a subset of machine learning that uses neural networks with multiple layers to analyze and learn from data. It can be used to improve the accuracy and efficiency of Digital Twins by enabling them to process large amounts of data and make more accurate predictions.	Improves accuracy and efficiency of Digital Twins by enabling large-scale data analysis and better predictions.
Convolutional Neural Networks (CNNs)	Image and video processing, pattern recognition	CNNs are a type of neural network that is particularly effective at image and video processing. They can be used to improve the accuracy of Digital Twins that involve visual data, such as simulations of manufacturing processes or traffic flows.	Improves accuracy of Digital Twins that involve visual data by enabling better pattern recognition and image processing.

Evolutionary Algorithms	Optimization, parameter search	Evolutionary Algorithms are a family of optimization algorithms that are inspired by the principles of biological evolution. They can be used to optimize Digital Twins by searching for the best parameters or configurations that produce the desired results.	Improves optimization of Digital Twins by enabling better parameter search and configuration for the desired results.
Fuzzy Logic	Uncertainty and imprecision handling	Fuzzy Logic is a mathematical framework that can deal with uncertainty and imprecision in data. It can be used to improve the accuracy of Digital Twins that involve incomplete or ambiguous data, such as simulations of human behavior or social systems.	Improves accuracy of Digital Twins that involve incomplete or ambiguous data by enabling better handling of uncertainty and imprecision in data.
Deep Reinforcement Learning	Learning through interactions, prediction improvement, complex behavior learning	Deep Reinforcement Learning is a combination of Reinforcement Learning and Deep Learning. It can be used to improve the accuracy of Digital Twins by training agents to learn complex behaviors through trial-and-error interactions with their environment.	Improves accuracy of Digital Twins by enabling better prediction and learning of complex

4. FUTURE DIRECTION

Looking ahead, we see several promising directions for future research. First, there is a need to develop more sophisticated AI algorithms that can handle complex and heterogeneous data from multiple sources. Second, there is a need to integrate AI with other emerging technologies such as block chain, Iota, and edge computing to enable more robust and secure digital twins. Third, there is a need to explore the ethical and social implications of using AI in digital twins, particularly in sensitive domains such as healthcare.

5. CONCLUSION

Our research has highlighted the potential of integrating new AI algorithms to improve digital twin technology, particularly in industries such as manufacturing and healthcare. By leveraging the proposed AI algorithms, we can enhance the accuracy, efficiency, and predictive power of digital twins, leading to better decision-making and optimization of operations. We have discussed various AI applications in digital twin technology and provided examples of successful implementations in real-world scenarios. However, there is still much work to be done in terms of exploring the full capabilities of AI for digital twins and addressing the challenges associated with data quality, scalability, and interpretability.

REFERENCES

[1] A. Rasheed, O. San and T. Kvamsdal, "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective," in IEEE Access, vol. 8, pp. 21980-22012, 2020, doi: 10.1109/ACCESS.2020.2970143

[2] Lu, Y., Liu, C., Kevin, I., Wang, K., Huang, H., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing, 61, 101837. Doi: https://doi.org/10.1016/j.rcim.2019.101837

[3] M., Virtually Intelligent Product Systems: Digital and Physical Twins, in Complex Systems Engineering: Theory and Practice, S. Flumerfelt, et al., Editors. 2019, American Institute of Aeronautics and Astronautics. p. 175-200.

[4] Z. Wang et al., "Mobility Digital Twin: Concept, Architecture, Case Study, and Future Challenges," in IEEE Internet of Things Journal, vol. 9, no. 18, pp. 17452-17467, 15 Sept.15, 2022, doi: 10.1109/JIOT.2022.3156028.

[5] Chiara Cimino, Elisa Negri, Luca Fumagalli, "Review of digital twin applications in manufacturing", Computers in Industry, Volume 113, 2019, 103130, ISSN 0166-3615, https://doi.org/10.1016/j.compind.2019.103130

[6] https://ch.mathworks.com/products/matlab.html

[7] Qinglin Qi, et al. "Enabling technologies and tools for digital twin", Journal of Manufacturing Systems, Volume 58, Part B, 2021, Pages 3-21, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2019.10.001.

[8] Sacks, R., Brilakis, I., Pikas, E., Xie, H., & Girolami, M. (2020). Construction with digital twin information systems. Data-Centric Engineering, 1, E14. doi:10.1017/dce.2020.16

[9] Benjamin Maschler, et al. "Transfer learning as an enabler of the intelligent digital twin", Procedia CIRP, Volume 100, 2021,Pages 127-132, ISSN 2212-8271, https://doi.org/10.1016/j.procir.2021.05.020.

[10] Kaur, M.J., Mishra, V.P., Maheshwari, P. (2020). The Convergence of Digital Twin, IoT, and Machine Learning: Transforming Data into Action. In: Farsi, M., Daneshkhah, A., Hosseinian-Far, A., Jahankhani, H. (eds) Digital Twin Technologies and Smart Cities. Internet of Things. Springer, Cham. https://doi.org/10.1007/978-3-030-18732-3_1

[11] Nasser Jazdi, et al. "Realization of AI-enhanced industrial automation systems using intelligent Digital Twins", Procedia CIRP, Volume 97, 2021, Pages 396-400, ISSN 2212-8271, https://doi.org/10.1016/j.procir.2020.05.257

[12] Chao Fan, et al. "Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management", International Journal of Information Management, Volume 56, 2021, 102049, ISSN 0268-4012, https://doi.org/10.1016/j.ijinfomgt.2019.102049.

[13] Samir Khan, et al. "On the requirements of digital twin-driven autonomous maintenance", Annual Reviews in Control, Volume 50, 2020, Pages 13-28, ISSN 1367-5788, https://doi.org/10.1016/j.arcontrol.2020.08.003.

[14] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, and M. Kudlur, ``TensorFlow: A system for large-scale machine learning,'' in Proc. 12th USENIX Symp. Operating Syst. Design Implement. (OSDI), 2016, pp. 265_283.

[15] F. Seide and A. Agarwal, ``CNTK: Microsoft's open-source deep-learning toolkit,'' in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Aug. 2016, p. 2135.

[16] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, ``Caffe: Convolutional architecture for fast feature embedding,'' in Proc. 22nd ACM Int. Conf. Multimedia, Nov. 2014, pp. 675_678.

[17] A. Gulli and S. Pal, Deep LearningWith Keras. Birmingham, U.K.: Packt, 2017.

[18] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, ``The WEKA data mining software: An update,'' ACM SIGKDD Explor. Newslett., vol. 11, no. 1, pp. 10_18, 2009.

[19] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba, ``OpenAI gym,'' 2016, arXiv:1606.01540. [Online]. Available: http://arxiv.org/abs/1606.01540

[20] Y. Duan, X. Chen, R. Houthooft, J. Schulman, and P. Abbeel, ``Benchmarking deep reinforcement learning for continuous control,'' in Proc. Int. Conf. Mach. Learn., 2016, pp. 1329_1338.

[21] Kaishu Xia, et al. "A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence", Journal of Manufacturing Systems, Volume 58, Part B, 2021, Pages 210-230, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2020.06.012.

[22] Botín-Sanabria, et al. "Digital Twin Technology Challenges and Applications: A Comprehensive Review". Remote Sens. 2022, 14, 1335. https://doi.org/10.3390/rs14061335

[23] Xin Ma, et al. "Artificial intelligence enhanced interaction in digital twin shop-floor", Procedia CIRP, Volume 100, 2021, Pages 858-863, ISSN 2212-8271, https://doi.org/10.1016/j.procir.2021.05.031.

[24] Computer Science > Networking and Internet Architecture.https://arxiv.org/abs/2105.07182 Accessed 2023-03-23

[25] Chao Fan, et al."Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster managemen"t, International Journal of Information Management, Volume 56, 2021, 102049, ISSN 0268-4012, https://doi.org/10.1016/j.ijinfomgt.2019.102049.

[26] Sacks, R., Brilakis, I., Pikas, E., Xie, H., & Girolami, M. (2020). Construction with digital twin information systems. Data-Centric Engineering, 1, E14. doi:10.1017/dce.2020.16

[27] Y. Xu,Y. Sun, X. Liu, andY. Zheng, ``Adigital-twin-assisted fault diagnosis using deep transfer learning,'' IEEE Access, vol. 7, pp. 19990_19999, 2019.

[28] H. Zhang, G. Zhang, and Q.Yan, ``Digital twin-driven cyber-physical production system towards smart shop-_oor,'' J. Ambient Intell. Humanized Comput., vol. 10, no. 11, pp. 4439_4453, Nov. 2019.

[29] C. Zhuang, J. Liu, and H. Xiong, ``Digital twin-based smart production management and control framework for the complex product assembly shop-_oor,'' Int. J. Adv. Manuf. Technol., vol. 96, nos. 1_4, pp. 1149_1163, Apr. 2018.

[30] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, ``Digital twindriven product design, manufacturing and service with big data,'' Int. J. Adv. Manuf. Technol., vol. 94, nos. 9_12, pp. 3563_3576, Feb. 2018.

[31] J. Liu, H. Zhou, G. Tian, X. Liu, and X. Jing, ``Digital twin-based process reuse and evaluation approach for smart process planning,'' Int. J. Adv. Manuf. Technol., vol. 100, nos. 5_8, pp. 1619_1634, Feb. 2019.

[32] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, and R. Harik, ``A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence,'' J. Manuf. Syst., Jul. 2020.

[33] P. Franciosa, M. Sokolov, S. Sinha, T. Sun, and D. Ceglarek, ``Deep learning enhanced digital twin for remote laser welding of aluminium structures,'' CIRP Ann. Manuf. Technol., vol. 69, no. 1, 2020.

[34] W. Wang, Y. Zhang, and R. Y. Zhong, ``A proactive material handling method for CPS enabled shop-_oor,'' Robot. Comput.-Integr. Manuf., vol. 61, Feb. 2020, Art. no. 101849.

[35] Y. Wang, S. Wang, B. Yang, L. Zhu, and F. Liu, ``Big data driven hierarchical digital twin predictive remanufacturing paradigm: Architecture, control mechanism, application scenario and bene_ts,'' J. Cleaner Prod., vol. 248, Mar. 2020, Art. no. 119299.

[36] S. Zhang, C. Kang, Z. Liu, J.Wu, and C. Ma, ``A product quality monitor model with the digital twin model and the stacked auto encoder,'' IEEE Access, vol. 8, pp. 113826_113836, 2020.

[37] C. Liu, L. Le Roux, C. Körner, O. Tabaste, F. Lacan, and S. Bigot, ``Digital twin-enabled collaborative data management for metal additive manufacturing systems,'' J. Manuf. Syst., May 2020.

[38] Y. Golizadeh Akhlaghi, A. Badiei, X. Zhao, K. Aslansefat, X. Xiao, S. Shittu, and X. Ma, ``A constraint multi-objective evolutionary optimization of a state-of-the-art dew point cooler using digital twins,'' Energy Convers. Manage., vol. 211, May 2020, Art. no. 112772

[39] R. Bansal, M. A. Khanesar, and D. Branson, ``Ant colony optimization algorithm for industrial robot programming in a digital twin,'' in Proc. 25th Int. Conf. Autom. Comput. (ICAC), Sep. 2019, pp. 1_5.

[40] S. Venkatesan, K. Manickavasagam, N. Tengenkai, and N. Vijayalakshmi, ``Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin,'' IET Electr. Power Appl., vol. 13, no. 9, pp. 1328_1335, Sep. 2019.

[41] Z. Liu, W. Chen, C. Zhang, C. Yang, and H. Chu, ``Data super-network fault prediction model and maintenance strategy for mechanical product based on digital twin,'' IEEE Access, vol. 7, pp. 177284_177296, 2019.

[42] Y. Ye, Q. Yang, F. Yang, Y. Huo, and S. Meng, ``Digital twin for the structural health management of reusable spacecraft: A case study,'' *Eng. Fract. Mech.*, vol. 234, Jul. 2020, Art. no. 107076.

[43] W. Luo, T. Hu, C. Zhang, and Y. Wei, ``Digital twin for CNC machine tool: Modeling and using strategy,'' J. Ambient Intell. Humanized Com- put., vol. 10, no. 3, pp. 1129_1140, Mar. 2019.

[44] F. Tao, M. Zhang, Y. Liu, and A. Y. C. Nee, ``Digital twin driven prognostics and health management for complex equipment,'' CIRP Ann., vol. 67, no. 1, pp. 169_172, 2018.

[45] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, ``Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation,'' J. Energy Storage, vol. 30, Aug. 2020, Art. no. 101557.

[46] W. Luo, T. Hu, Y. Ye, C. Zhang, and Y. Wei, ``A hybrid predictive maintenance approach for CNC machine tool driven by digital twin,'' Robot. Comput.-Integr. Manuf., vol. 65, Oct. 2020, Art. no. 101974.

[47] W. Booyse, D. N.Wilke, and S. Heyns, ``Deep digital twins for detection, diagnostics and prognostics,'' Mech. Syst. Signal Process., vol. 140, Jun. 2020, Art. no. 106612.

[48] P. E. Leser, J. E. Warner, W. P. Leser, G. F. Bomarito, J. A. Newman, and J. D. Hochhalter, ``A digital twin feasibility study (Part II): Nondeterministic predictions of fatigue life using in-situ diagnostics and prognostics,'' Eng. Fract. Mech., vol. 229, Apr. 2020, Art. no. 106903

[49] H. Kim, C. Jin, M. Kim, and K. Kim, ``Damage detection of bottom-set gillnet using arti_cial neural network,'' Ocean Eng., vol. 208, Jul. 2020, Art. no. 107423.

[50] A. Piros, L. Trautmann, and E. Baka, ``Error handling method for digital twin-based plasma radiation detection,'' Fusion Eng. Design, vol. 156, Jul. 2020, Art. no. 111592.

[51] H. Zhang, Q. Yan, and Z.Wen, ``Information modeling for cyber-physical production system based on digital twin and automationml,'' Int. J. Adv. Manuf. Technol., pp. 1_19, Mar. 2020.

[52] M. G. Kapteyn, D. J. Knezevic, D. B. P. Huynh, M. Tran, and K. E. Willcox, ``Data-driven physics-based digital twins via a library of component-based reduced-order models,'' Int. J. Numer. Methods Eng., Jun. 2020

[53] P. Jain, J. Poon, J. P. Singh, C. Spanos, S. R. Sanders, and S. K. Panda, ``A digital twin approach for fault diagnosis in distributed photovoltaic systems,'' IEEE Trans. Power Electron., vol. 35, no. 1, pp. 940_956, Jan. 2020.

[54] A. Coraddu, L. Oneto, F. Baldi, F. Cipollini, M. Atlar, and S. Savio, ``Data-driven ship digital twin for estimating the speed loss caused by the marine fouling,'' Ocean Eng., vol. 186, Aug. 2019, Art. no. 106063