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A Systematic Review: Digital Twin in Healthcare

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Abstract: In recent years, patient-specific, precise treatment and diagnosis have been needed in order to advance efficiency in the healthcare domain. Digital Twin (DT) is a technology that pin-points the Industry 4.0 Revolution. Apart from the manufacturing and automotive industries, DTs in the healthcare sector are also advancing. Traditional analysis of clinical scans uses biomarkers, wherein the diagnostic stage involves numerous scans before the actual treatment is provided. The healthcare staff mostly depends on indigenous knowledge, which is insufficient in the face of unforeseen circumstances. Lack of personalised medication and treatment is still in the infant stages of development.

In this paper, we have analysed and reviewed various method- ologies, technologies and proposed solutions for case-specific scenarios of Digital Twin. The correlation between personalised medication and the impact of Digital Twin in the healthcare domain is among our findings. The framework and software are used to provide micro-services, better prediction, and an interface to the ML and DT models. By incorporating these models, optimal, individualised care can be administered in a healthcare environment.

Index Terms: Convolutional Neural Network, Digital Twin, Human Anatomy, User-Friendly Frameworks.

I. INTRODUCTION

The Digital Twin (DT) concept entails creating a digital copy of real-world physical assets or processes and establish- ing a real-time link between the actual and digital entities.The created twins allow for near-real-time monitoring. This innovation is at the forefront of the Industrial 4.0 revolution, facilitated by IOT and data analytics. NASA pioneered the concept of ”twin” in its Apollo Space Program. This pro-gramme involved the construction of a ground-based space vehicle that simulated and mirrored its physical counterpartin space. This was the first instance of a digital twin that appeared. Dr. Grieves had informally proposed the concept of DT in 2002, stating that a digital twin consists of a physical and virtual product as well as a bidirectional data connection. This information from the physical entity is fed into the digitaltwin, and the digital twin's processed information is delivered to the physical entity. Many technologies, such as AI, cloud computing, the 5G network, big data, and edge computing, make it possible to combine physical and digital entities. The integration of the digital twin with the physical asset is still a sophisticated process that is still in its early phases.

The amount of data that can be used in the manufacturing, healthcare, and smart city environments has expanded thanks to IoT. The IoT's rich environment, when combined withdata analytics, offers a vital resource for preventive analytics and fault detection, to name just two, as well as the long-term health of manufacturing processes and the development of smart cities. It also supports anomaly detection in treat-ing patients, fault detection, and traffic control in a smartcity. A digital twin of a person, which provides a real- time examination of the body, is one potential future use. A Digital Twin, which is being utilised to simulate the effectsof some medications, is a more realistic application. A Digital Twin is used in a different application to plan and carry out surgical treatments. [1] The Digital Twin within the medical environment has the potential along with AI to make life saving decisions based on real-time and historical data

The remainder of the paper is organised as follows: Section 2 presents the Contributions of this paper. In Section 3, we have explored the Digital Twin technology from various perspectives, such as framework, human anatomy, and modelsbased. The stages in Design Flow of a DT creation is shown in Section 4. We have concluded the paper and provided our insights for future enhancements in Section 5.

II. CONTRIBUTIONS

Through this comprehensive study, we intend to demonstratedifferent aspects of Digital Twin and its adoption in various domains. The contribution of this paper is twofold.

We classify the literary works of the Digital Twin technologyin three categories, namely-

1) Digital Twin based on Conceptual Framework.
2) Digital Twin based on Customised Diagnosis and Personalised Medication.

In this survey paper, we have analyzed and reviewed the methodologies, technology, proposed solutions and challengesin each of the above mentioned categories and presented the same.

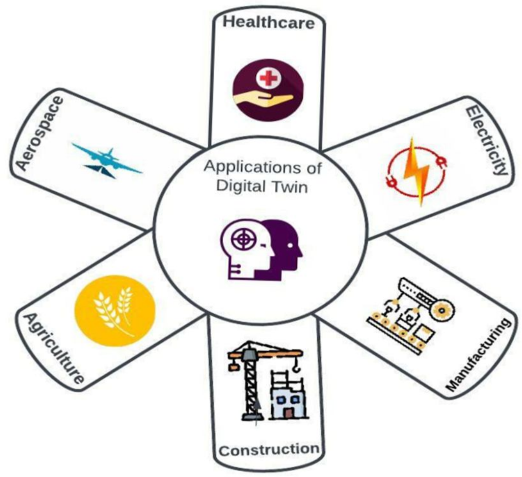

Fig. 1: Applications of Digital Twin in various domains

III. RELATED WORK

Valk et. al. [2] had introduced an agent-based digital twin framework in the healthcare domain. It utilised the theory of mirror worlds and derived an application scenario for trauma management. The intervention of software agents, along with a cyber-physical connection, is incorporated for DT creation. Ethical and legal approval is a major concern since it indulges patients' privacy and medical tool schema.

Kolekar et al. (2012), on the other hand, created a framework that analyses data from various sources and provides a multilayered model based on micro-facilities and web applications. Their motivation to build the framework comes from the concept of the digital counterpart of healthcareservices for lung cancer survival analysis. This framework can be employed as a reference system for practitioners and medical aid. These services are only accessible in the organization's private cloud, which limits the reachability and scope of the cloud services.

There is a need for an open-source software platform for the integration and simulation of scalable models that supports a decentralized, community-based model building process for distributed model building and integration. To implement precision medicine, Masison et. al. [3] had proposed a modular software design framework for the construction of computational modelling technology. It presents a case study of a respiratory fungal infection by the fungus Aspergillus fumigatus in an animal model.

Wickramasinghe et. al. [4] had proposed the grey, surrogate,and black box models of a digital twin. The Black Box model relied on rich datasets of physiological, demographic and clinical records. When a uterine cancer patient was introduced, a digital twin that was most equivalent to the patient was obtained. This way, case-specific individualised cancer treatment could be offered. On the other hand, there is still a lack of conviction for using black box computation, as wellas data and privacy concerns.

Wickramasinghe et al. (cited as Wickramasinghe 2022 Digital) emphasised the significance of incorporating the digital twin into dementia treatment for improved detection and prevention. The thriving datasets on dementia cases, the data from the IOT devices and the patient's progressionof disease, the treatment provided, and the risk factors are entered into a Decision Support System(DSS) . Machine Learning or Deep Learning algorithms use the input data to identify and match the most similar cases into 'model patient'. The understanding of previous cases is obtained by the physician using digital twins and hence presents the diagnosis. The hurdles to this consist of complexity and the increased cost of implementation and development.

Samuel D. Okegbile and Jun Cai [5] had introduced a connectivity scheme between a Human-Virtual pair. This scheme is blockchain and Federated Learning enabled to avert data exposure and other attacks. The connectivity issue is defined as a Markov decision process (MDP), andto obtain a solution to this, a deep reinforcement learning(DRL) algorithm using the deep deterministic-policy gradient (DDPG) approach was developed. The outcome was exhibited through simulations, which optimised the connectivity processand lowered its cost. However, this scheme evades to include the accuracy of the human-virtual twin model.

Laamarti et. al. [6] had proposed a systematic frameworkfor DT with a user-response architecture. This framework gathers and examines the data of medical devices using CNN. A mobile app was developed with a feedback mechanism.The framework is only useful for a short period of time and provides limited accuracy in mobile interfaces.

Gillette et. al. [7] had proposed the idea of developinga digital twin of the human heart that mimics its electrophysiology (CDTs). This will facilitate the developmentof superior therapeutic interventions in a safe and economical manner. A critical point to remember is that more precise clinical therapy cannot be achieved with a sophisticated bio-physical simulation of the heart and an electrocardiogram (ECG) model.

According to Barricelli et. al. [8], it is critical to measure fitness-related metrics that characterise an athlete's daily activities. After gathering sufficient data, the DT first forecasts the physical twin's performance during training and, in the event of a less-than-ideal outcome, advises behavioural changes for the athlete. The team of the athlete is connectedto SmartFit, a software system that aids coaches and trainers in keeping track of and managing athletes' fitness activity and outcomes through wearable IoT sensors that are integrated with various applications.

Bjelland et. al. [9] had proposed a macro-level digital twin for arthroscopic surgery by utilising case-specific patient information and techniques for interactive soft tissue simulation during surgery. There is an integration of patient specific diagnostic information and sensor data. This aids medical professionals in broadening their understanding of surgery on specific patients. However, a crucial aspect ofintroducing the dynamic behaviour of the knee joint in the digital twin has not been discussed.

Multiple sclerosis is an autoimmune disease of the brainand spinal cord. Voigt et. al. [10] had focused on managing this disease by developing its digital twin. This twin enables the provision of patient-specific therapies, thereby preventing disease progression. Analysis using AI can be done on variousdisease parameters that include biomarkers, clinical data and medical records. There are still a lot of challenges whichinclude security and privacy of data, cost and complexity.

Johannes Möller and Ralf Pörtner [11] have proposed an in vitro tissue culture technique that utilises mathematical models. Tissue culture can be depicted using these models in a silico representation which constitutes the digital twin. The authors discovered that incorporating large amounts of data and experience from related systems into the digital twin framework makes donor-specific systems easier to implement.Through this approach, tissue culture systems with reduced costs and less time can be enforced in industries. However,it is observed that there is a requirement for personalisedprocessing, and the researchers have to be educated in aninterdisciplinary system.

Sadman Sakib Akash and MD Sadek Ferdou [12] had suggested a Blockchain-based DT for healthcare to improve security and privacy for sensitive patient data that is vulnerable to malicious behavior. This article mostly addressed the security of healthcare data. The crucial component of DT , a rapidly developing technology, is that it does not describe the medications and treatments for ailments.

Safa Elkefi et. al. [13]had advanced as a rapidly growing area, the use of DTs for management and healthcare services. This is seen in the scant material available to support this technique. However, the use of DTs to guarantee patient security and welfare in a structured system is growing. Therefore, future research should look into the potential of DT technology to address the issues facing health care systems and enhance their performance. In order to assure better design and a more positive impact on patient and doctor experiences, such technologies should also incorporatehuman aspects and ergonomic concepts.

Khan et. al. [14] had outlined how Digital Twin (DT), a digital depiction of the real system, is revolutionising our lives. Cyber Physical Systems (CPS), the Internet of Things (IoT), Big Data, Edge Computing (EC), Artificial Intelligence (AI), and Machine Learning (ML), among other technologies, were all combined to create DT. DTs are created to improvea variety of applications in business, medicine, smart cities, smart homes, etc. It is still in the early stages of development.

Li et. al. [15] present an approach to predict certain treatments during the first 24 hours of sepsis. A hybrid approach combining agent-based modelling and simulation, discrete-event simulation, and a Bayesian network model is used to develop the model and simulate the patient and the environment across multiple stages. The observed patient response and the digital twin's predicted response are both statistically compared. The development of AI models thatare debugged, verified, and validated is slow and error-prone, which is the drawback of the model.

We need to completely understand the scope and extentof CVD research to empower it. Coorey et. al. [16] describe the 'digital twin' research, emphasising the uses of the term and concept within a CVD-related context, identifying thedisciplines contributing to it, and elaborating on the emerging challenges for the advancement of digital twin research within the wider context of precision medicine. The prospect has been raised for AI and digital twin technology to gather intelligence from huge volumes of patient data for enhancing the patient experience, care coordination, scheduling, and other service-oriented operations at the healthcare facility level.

The severity of pneumonia patients is detected to ensure smooth functioning in Intensive Therapy Units(ITU) so that highly prioritised patients can be given ventilation. Chakshu et. al. [17] have proposed a digital-twin model built on pre-trained deep learning models using data from pneumonia patients.The model seems to give better results than existing methods and can be modified accordingly, where COVID-19 patients priorities can also be determined. The prediction accuracy appears to be excellent and can still be improved.

Chakshu et. al. [18] propose an approach to detect the seriousness of carotid artery stenosis where the video of a human face is linked to the carotid arteries, creating a semi active digital twin model. The nature of blood flow through the arteries causes a subtle head vibration, which indicates the severity of carotid stenosis. A computer vision algorithm is adopted to learn the head vibrations, which are compared against the virtual vibration data generated from the coupled computational blood flow or vibration model to determine the best fit between in vivo and virtual data. This result will clearly specify that the model is accurate. If sophisticated setups are used, this model can be used to indicate the severity of a large number of blood flow-related diseases. A little improvement can ensure that it is a clinically usable platform.

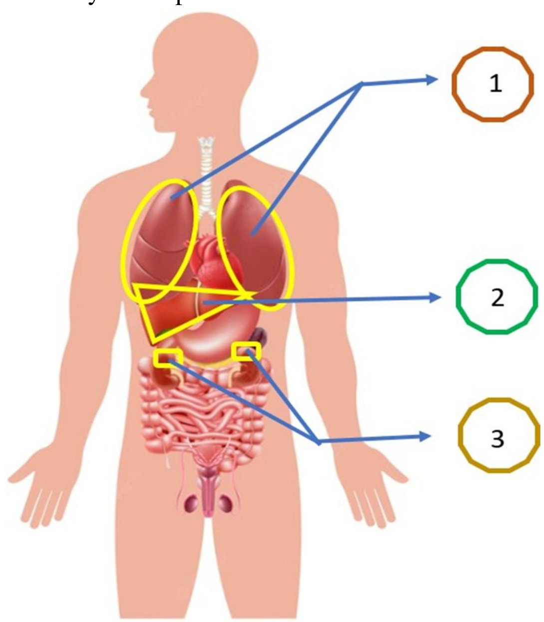

Fig. 2: Batch et. al. [25] had used NLP classification and Deeplearning techniques to identify tumors in 1)Lungs 2)Liver 3)Adrenal glands using CT scans of patients

Developing a cancer digital twin: Supervised metastases detection from consecutive structured radiology reports// As shown in Fig. 2, Batch et al. (2001) used supervised and unsupervised classification models, as well as NLP labeling, to detect cancer cells in specific human organs. The cumulative results of the models are highly accurate for the prediction of tumors. The accuracy of these models substantially depends on the access and highest-resolution representation of patient's data.

Bjo¨rnsson et. al. [26] proposed DT as a solution to the problem of patient-tailored medicine. They had built vast copies of patients' DT based on deep learning models and unique disease-related irregularities. The drug with the best effect can be analysed for better treatment. The lack of medical, social, and scientific approaches are the major concerns.

Wang et. al. [27] had proposed the integration of welding with deep learning techniques as a remedy to the limitations of the traditional welding process. The CNN models are used to capture and monitor real-time welding progress. This method was used to supervise weld joint growth and yield good quality. The crucial welding parameters such as heat transfer, flow of fluids, etc. are not considered in this model.

According to Chakshu et. al. [24] better accurate solutions for inverse analysis of linear issues have been proposed and deployed, and the rise in patient data presents a fantastic opportunity to improve the current health care infrastructure. In order to provide data, the blood pressure is calculated using the Long Short Term Memory (LSTM). The abdominal aortic aneurysm (AAA) and its severity are detected using neural networks and the inverse analysis system constructed in this manner. However, these techniques fall short or are ineffective for nonlinear systems, such as blood flow in the cardiovascular system, which exhibits a significant degree of systemic circulation.

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Subramanian et. al. [22] 2022 Digital) have mentioned how current developments in machine-learning (ML) and deep-learning (DL) methods had been influenced by emotion recognition (ER) in the healthcare industry. Building such ER systems in real time, however, poses technical difficulties due to restricted datasets, occlusion and lighting concerns, incorrect emotion classification, etc. To address this problem, we developed an easy-to-use, effective, and flexible emergency room system that uses a web camera to capture and process photos in real time. Incrementing that, an end-to-end framework that integrates an ER system with a digital twin setup is used, enabling the projected result to be examined and tested before receiving the finest care for an individual before it develops into a life-threatening illness.

XU et. al. [20] had suggested using a Deep Neural Network(DNN) model to forecast a more accurate method of ailment treatment. The trained diagnosis model is then used for patient monitoring and proactive maintenance, utilising deep transfer learning. The diagnosis approach is predicted usinga variety of deep learning algorithms. However, because this digital twin technology is still developing, the models thatare created will not be ideal for situations that are changing rapidly.

Hussain et. al. [23] had stated that electroencephalography (EEG) monitoring is regarded as an important marker for the diagnosis of stroke and that neurological impairmentis a prevalent disease seen in the stroke population. This work uses EEG data and machine learning models to create a digital twin for stroke victims as a proof-of-concept for a ”digital twin” in healthcare. According to the statistical analysis, the motor and cognitive states of stroke patients and healthy people can be distinguished using the updated brain-symmetry index, theta, and delta activities. Support vector machines (SVM) identified the EEG feature dataset with better accuracy for categorising the stroke and the controlgroup using the machine learning approach. The clinical decision-making process for stroke prevention strategies and post-stroke care may be aided by this healthcare digital twinstructure.

TABLE I: Analysis of Literature Survey

Author	Year	Approach	Learning Technique	Dataset	Usecases(or)Applications	Accuracy
Martinez-Velazquez et.al [19]	2019	Deep neural model	CNN	PTB diagnostic ECG database	Detects Ischemic Heart Disease(IHD) in theheart	85.77
Yan Xu et. al. [20]	2019	Deep neural network based model	Deep transfer learning (DFDD)	-	Provides a new pattern model for fault diagnosis	97.96
Jun Zhang et. al [21]	2020	Deep neural model	LSTM	Software Assurance Reference Dataset(SARD)	Forecasts a person’s state of health andoffer solutions for avariety of clinical problems	-
Barathi Subramanianet. al. [22]	2020	Data-driven method	CNN	Real time Weld data	Supervise weld joint growth and yield good quality	-
Hussain et. al [23]	2021	Machine learning approach	-	EEG dataset	Digital twin model to prevent stroke and treatment post stroke	76
Chakshu et .al [24]	2021	Inverse analysis	CNN,LSTM	Virtual patients’ database	Abdominal aortic aneurysm (AAA) and its severity is detected	90.58
Subramanian et. al. [22]	2022	Automatic emotion detection from EEG signals	Gradient Boost-ing,RNN,CNN,etc.	Custom dataset in real time(5991 images from3 volunteers)	Emotion Recognition for best personal heathcare	99.9
Batch et. al. [25]	2022	Word embedding and NLP labelling	CNN(Simple ,aug-mented),RNN,Ensemble method	Memorial Sloan Kettering Cancer Center CT scans(2009-2021)	Analyse cancer advancement and identify tumors in specific organs	99.95

Zhang et. al. [21] had stated that Internet of Things (IoT) technology and AI algorithms are used to forecast a person's state of health and offer recommendations for a variety of clinical problems. The proper cyber resilience technologies and policies must be implemented and upheld to support healthcare digital twins. A key technique for cyber resilience in healthcare digital twins is vulnerability detection. Deeplearning (DL) has recently been used to overcome the shortcomings of conventional machine learning in the area of vulnerability identification. Due to the size and complexity of the healthcare digital twin, a fully automatic solution is truly required to aid in the cyber resilience check in real-worldsettings by applying appropriate DL-based methodologies for vulnerability detection.

Velazquez et. al. [19] has proposed an architecture of Cardio Digital Twin to detect a heart condition(IHD). Thetwin obtains patient data from various sensors and medical documents. This data is fused, standardized and analysed using a data fusion model. CNN was used to classify myocardial and non myocardial segments, for which an accuracy of 85.77% was obtained. A model without enough accuracy could be replaced by a Cardio Twin. The twin could be advanced by including more sensor data other than ECG data alone.

Shamanna et. al. [28] have proposed a Digital Twin enabled Twin Precision Nutrition(TPN) program to monitor the variation in HbA1c, insulin resistance and other glucose profile metrics. The advancement of the disease leads to highermedication usage and costs. Meal intake and daily continuous glucose monitor(CGM) were provided as input to the TPN machine learning models. This data was gathered from body sensors and other mobile applications. Based on the patient specific input, guided nutrition is offered to the patient. The patients showed significant results through decreasingHbA1c and phasing out the use of diabetic medications. However, this program included a limited study populationand duration, which couldn't justify the alleviation of diabetes.

The development and testing of drugs is a formidable task. Kalyanasundaram Subramanian [29] had generated a digital liver by analysing the anatomy of a human liver. He createda liver DT based on mathematical formulas and hierarchical theory.It was used to test and monitor the molecular effectsof the drugs on the liver. The model discards the chemical toxicities in individuals and lack of integration of outcomesto AI knowledge.

IV. DESIGN

The Design Flow consists of 6 stages, as shown in Fig. 3.In the first stage, real-time, precise data will be gathered. The data can be in any format (PDF, PNG, or SQL). In the next stage, the collected data will be cleaned to remove duplicates and erroneous content. In the third stage, the data will be processed to extract useful information.

In the next stage, the information will be fed to ML techniques to generate the model. This model is used for recognizing patterns in the processed data. In the fifth stage, a DT will be constructed for research and patient care. At the last stage, the generated DT and models are used for prediction and visualisation.

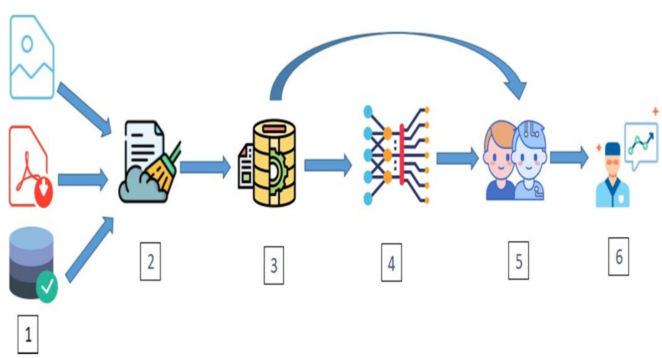

Fig. 3: Six stages of design flow:1)Data Collection 2)Data Cleaning 3)Data Processing 4) ML model generation 5)Cre- ation of DT 6)Prediction and Visualisation

V. CONCLUSION AND FUTURE ENHANCEMENTS

The introduction of Digital Twins in healthcare has enabledin improvising personalised treatment and therapy decisions [30]. The systems in healthcare involve higher levels of non- linearity, and hence we utilise various neural network models like recurrent neural network using virtual data. The patient's medical records, sensor data, ECG, and EEG are the different sources of input data. The Machine Learning and Deep Learn-ing models utilise this data to run on the digital twins, and the most accurate and optimal treatment plan is administered tothe patient.

The frameworks act as an interface to the ML models for user interaction, better prediction, and provide microservices. Prediction and monitoring before the condition of the patient escalates are also aided by the DTs using the models. DT are used to simulate healthcare environments [31], [32], medical devices [33] and even complex human anatomy for better research and efficient management of services.

However, the data and parameters considered are sometimes confined, and there is a need to expand the scope of sensor data. The medical conditions are also restricted to individual anomalies, and there may be chances that the outcome may vary when multiple conditions are considered in a real-time en- vironment. The aspects of dealing with legal and ethical issuesare limited. The cost of implementation and the insufficiency of enriched technology are the setbacks of DT technology.

REFERENCES

[1] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," IEEE access, vol. 8, pp. 108952–108971, 2020.
[2] A. Croatti, M. Gabellini, S. Montagna, and A. Ricci, "On the integration of agents and digital twins in healthcare," Journal of Medical Systems, vol. 44, no. 9, pp. 1–8, 2020.
[3] J. Masison, J. Beezley, Y. Mei, H. A. L. Ribeiro, A. C. Knapp, L. Sordo Vieira, B. Adhikari, Y. Scindia, M. Grauer, B. Helba, et al., "A modular computational framework for medical digital twins," Pro- ceedings of the National Academy of Sciences, vol. 118, no. 20, p. e2024287118, 2021.
[4] N. Wickramasinghe, P. P. Jayaraman, A. R. M. Forkan, N. Ulapane, R. Kaul, S. Vaughan, and J. Zelcer, "A vision for leveraging the concept of digital twins to support the provision of personalized cancer care," IEEE Internet Computing, vol. 26, no. 5, pp. 17–24, 2021.
[5] S. D. Okegbile and J. Cai, "Edge-assisted human-to-virtual twin connec- tivity scheme for human digital twin frameworks," in 2022 IEEE 95th Vehicular Technology Conference:(VTC2022-Spring), pp. 1–6, IEEE, 2022.
[6] F. Laamarti, H. F. Badawi, Y. Ding, F. Arafsha, B. Hafidh, and A. El Sad- dik, "An iso/ieee 11073 standardized digital twin framework for health and well-being in smart cities," IEEE Access, vol. 8, pp. 105950–105961, 2020.
[7] K. Gillette, M. A. Gsell, A. J. Prassl, E. Karabelas, U. Reiter, G. Reiter, T. Grandits, C. Payer, D. Sˇtern, M. Urschler, et al., "A framework for the generation of digital twins of cardiac electrophysiology from clinical 12-leads ecgs," Medical Image Analysis, vol. 71, p. 102080, 2021.
[8] B. R. Barricelli, E. Casiraghi, J. Gliozzo, A. Petrini, and S. Valtolina, "Human digital twin for fitness management," Ieee Access, vol. 8, pp. 26637–26664, 2020.
[9] Ø. Bjelland, B. Rasheed, H. G. Schaathun, M. D. Pedersen, M. Steinert, A. I. Hellevik, and R. T. Bye, "Towards a digital twin for arthroscopic knee surgery: A systematic review," IEEE Access, 2022.
[10] I. Voigt, H. Inojosa, A. Dillenseger, R. Haase, K. Akgu¨n, and T. Ziemssen, "Digital twins for multiple sclerosis," Frontiers in immunol- ogy, vol. 12, p. 669811, 2021.
[11] J. Mo¨ller and R. Po¨rtner, "Digital twins for tissue culture tech- niques—concepts, expectations, and state of the art," Processes, vol. 9, no. 3, p. 447, 2021.
[12] S. S. Akash and M. S. Ferdous, "A blockchain based system for healthcare digital twin," IEEE Access, 2022.
[13] S. Elkefi, O. Asan, et al., "Digital twins for managing health care systems: Rapid literature review," Journal of Medical Internet Research, vol. 24, no. 8, p. e37641, 2022.
[14] S. Khan, T. Arslan, and T. Ratnarajah, "Digital twin perspective of fourth industrial and healthcare revolution," IEEE Access, vol. 10, pp. 25732– 25754, 2022.
[15] A. Lal, G. Li, E. Cubro, S. Chalmers, H. Li, V. Herasevich, Y. Dong, B. W. Pickering, O. Kilickaya, and O. Gajic, "Development and verifica- tion of a digital twin patient model to predict specific treatment response during the first 24 hours of sepsis," Critical care explorations, vol. 2, no. 11, 2020.
[16] G. Coorey, G. A. Figtree, D. F. Fletcher, V. J. Snelson, S. T. Vernon, D. Winlaw, S. M. Grieve, A. McEwan, J. Y. H. Yang, P. Qian, et al., "The health digital twin to tackle cardiovascular disease—a review of an emerging interdisciplinary field," NPJ digital medicine, vol. 5, no. 1, pp. 1–12, 2022.
[17] N. K. Chakshu and P. Nithiarasu, "An ai based digital-twin for priori- tising pneumonia patient treatment," Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, p. 09544119221123431, 2022.
[18] N. K. Chakshu, J. Carson, I. Sazonov, and P. Nithiarasu, "A semi- active human digital twin model for detecting severity of carotid stenoses from head vibration—a coupled computational mechanics and computer vision method," International journal for numerical methods in biomedical engineering, vol. 35, no. 5, p. e3180, 2019.
[19] R. Martinez-Velazquez, R. Gamez, and A. El Saddik, "Cardio twin: A digital twin of the human heart running on the edge," in 2019 IEEE International Symposium on Medical Measurements and Applications (MeMeA), pp. 1–6, IEEE, 2019.
[20] Y. Xu, Y. Sun, X. Liu, and Y. Zheng, "A digital-twin-assisted fault diagnosis using deep transfer learning," Ieee Access, vol. 7, pp. 19990– 19999, 2019.
[21] J. Zhang, L. Li, G. Lin, D. Fang, Y. Tai, and J. Huang, "Cyber resilience in healthcare digital twin on lung cancer," IEEE Access, vol. 8, pp. 201900–201913, 2020.
[22] B. Subramanian, J. Kim, M. Maray, and A. Paul, "Digital twin model: A real-time emotion recognition system for personalized healthcare," IEEE Access, vol. 10, pp. 81155–81165, 2022.
[23] I. Hussain, M. A. Hossain, and S.-J. Park, "A healthcare digital twin for diagnosis of stroke," in 2021 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON), pp. 18–21, IEEE, 2021.
[24] N. K. Chakshu, I. Sazonov, and P. Nithiarasu, "Towards enabling a cardiovascular digital twin for human systemic circulation using inverse analysis," Biomechanics and modeling in mechanobiology, vol. 20, no. 2, pp. 449–465, 2021.
[25] K. E. Batch, J. Yue, A. Darcovich, K. Lupton, C. C. Liu, D. P. Woodlock, M. A. K. El Amine, P. I. Causa Andrieu, L. Gazit, G. H. Nguyen, et al., "Developing a cancer digital twin: Supervised metastases detection from consecutive structured radiology reports," Frontiers in artificial intelligence, p. 26, 2022.
[26] B. Bjo¨rnsson, C. Borrebaeck, N. Elander, T. Gasslander, D. R. Gawel, M. Gustafsson, R. Jo¨rnsten, E. J. Lee, X. Li, S. Lilja, et al., "Digital twins to personalize medicine," Genome medicine, vol. 12, no. 1, pp. 1– 4, 2020.

[27] Q. Wang, W. Jiao, and Y. Zhang, "Deep learning-empowered digital twin for visualized weld joint growth monitoring and penetration control," Journal of Manufacturing Systems, vol. 57, pp. 429–439, 2020.
[28] P. Shamanna, B. Saboo, S. Damodharan, J. Mohammed, M. Mohamed, T. Poon, N. Kleinman, and M. Thajudeen, "Reducing hba1c in type 2 diabetes using digital twin technology-enabled precision nutrition: a retrospective analysis," Diabetes Therapy, vol. 11, no. 11, pp. 2703– 2714, 2020.
[29] K. Subramanian, "Digital twin for drug discovery and development—the virtual liver," Journal of the Indian Institute of Science, vol. 100, no. 4, pp. 653–662, 2020.
[30] M. N. Kamel Boulos and P. Zhang, "Digital twins: from personalised medicine to precision public health," Journal of Personalized Medicine, vol. 11, no. 8, p. 745, 2021.
[31] H. Elayan, M. Aloqaily, and M. Guizani, "Digital twin for intelligent context-aware iot healthcare systems," IEEE Internet of Things Journal, vol. 8, no. 23, pp. 16749–16757, 2021.
[32] A. Karakra, F. Fontanili, E. Lamine, J. Lamothe, and A. Taweel, "Perva- sive computing integrated discrete event simulation for a hospital digital twin," in 2018 IEEE/ACS 15th international conference on computer systems and Applications (AICCSA), pp. 1–6, IEEE, 2018.
[33] T. Erol, A. F. Mendi, and D. Dog˘an, "The digital twin revolution in healthcare," in 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), pp. 1–7, IEEE, 2020.