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Harnessing the Power of Digital Twins: A Paradigm Shift in Precision Medicine and Cancer Biology

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ABSTRACT

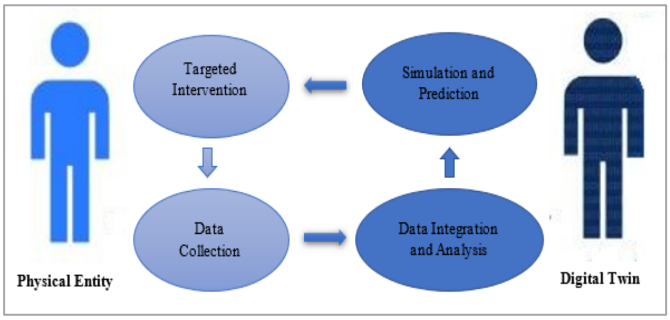
In recent years, the potential use of digital twins (DTs) in healthcare sectors is becoming a growing research area that can lead to more individualized patient care. In this regard the use of precision medicine towards personalized treatment is emerging as promising approach that takes into account of individual variability in genes, environment and lifestyle of each person. Moreover, precision medicine provides a framework for designing a targeted treatment for individual patients by combining clinical and demographic information as well as biomarkers and medical imaging data. The process of diagnosing and treating patients, particularly in the context of cancer treatment, involves multiple steps and can also have certain limitations. Introducing DTs in personalized treatment planning, including the use of precision medicine, could support and enhance the cancer care. Although the digital twin model has the potential to accurately diagnose cancer, advanced monitoring systems are necessary for commercial use.

INTRODUCTION

A digital twin is a virtual clone of a physical object or a human body, including any biological organ or a process that keeps itself constantly updated with changes in the real world. The terminology "digital twins" was first coined within medical imaging techniques (Popa et al., 2021). Swift advancements in precision medicine have improved patient care and revolutionized clinical research, diagnosis, and cancer treatment. However, this growing technology faces a few challenges to achieve a flawless, personalized approach (Wickramasinghe et al., 2021). Precision oncology aims to enhance patient diagnosis and treatment by delving deeply into individual diseases for more precise healthcare outcomes and applications (Stahlberg et al., 2022). Digital twin involvement can provide a crucial solution in decision-making by providing more efficient and precise tailored treatments for individual cancer patients (Wickramasinghe et al., 2021). Digital twins assist in decision-making by incorporating cloud computing, artificial intelligence, and machine learning technologies for more precise outcomes (Meraghni et al., 2021). Health digital twins merge virtual models with real-time data using cloud and 5G, enhancing performance and predicting failures, even in oncology (Coorey et al., 2022). The synergy of digital twin, AI, and patient perspectives enhances analytics for effective cancer management, including diagnosis, prognosis, and treatment selection (Kaul et al., 2023). The proposition of cancer patient digital twin was initiated by a collaboration that funded five projects; i) simulating one million pancreatic cancer patients to guide treatment, ii) self-learning platforms for personalized treatment of melanoma, iii) an adaptive digital twin approach for monitoring resistance and treatment response, iv) a patient-specific multiscale digital twin for the exploration of optimal treatment pathways for non-small cell lung cancer, v) virtual cancer digital twin approaches, aimed to develop approaches that would advance the creation of cancer patient DTs (Stahlberg et al., 2022). DTs applications in cancer research emerged recently, utilizing advancements in cancer research, mathematics, and computer science. These models simulate tumor behavior, aiding personalized cancer treatment (Wu et al., 2022). Probabilistic digital twins, employing a Bayesian framework, manage uncertainty in data and model predictions, enabling more robust optimization of the physical object's performance compared to deterministic counterparts (Lorenzo et al., 2023) (Figure 1 & 2).

Figure 1

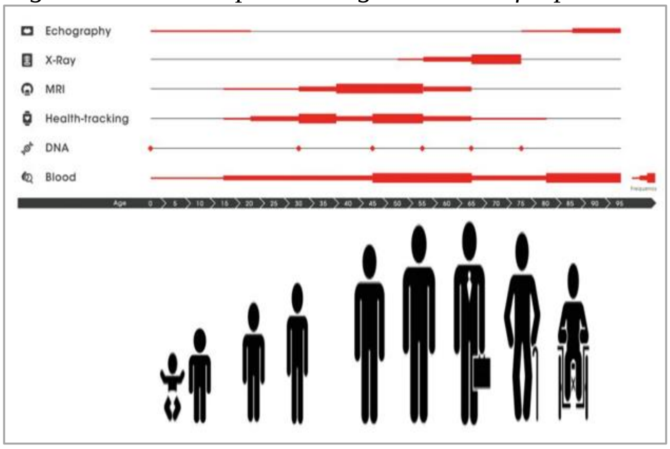
Data collection to intervention.



Imagine a flawless digital clone replicating its surroundings, extracting health insights from linked databases via smart sensors that offer precise diagnoses, predictions, and suggestions to enhance our health understanding by leveraging technologies such as cloud computing (Shengli & Update, 2021).

Figure 2

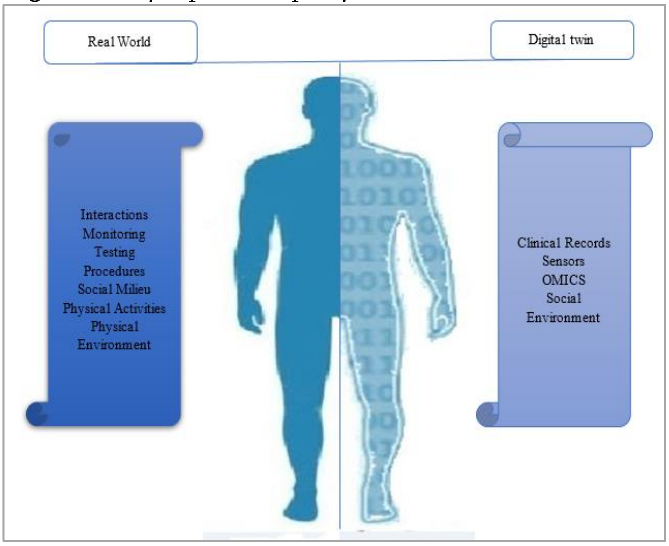
Digital twin data capture along the entire life span.



The development of precise simulation models with cloud databases aids oncologists in monitoring cancer patients by utilizing available data to recognize model patterns related to tumor development and treatment responses (Mourtzis et al., 2021). The digital twin significantly impacts the cost and speed of drug development. Simulations can be run virtually, enhancing drug formulation without the need for extensive physical experiments (Figure 3).

Figure 3

Digital twin for patient-specific care.

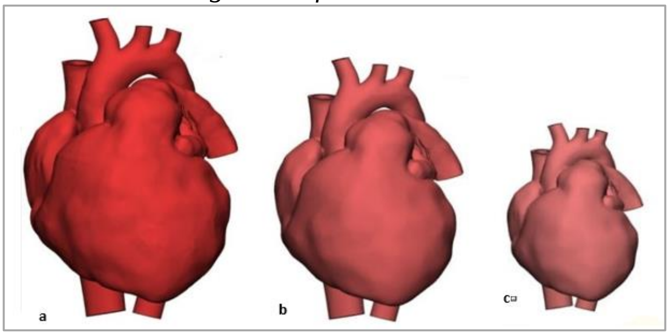


Digital Twins in Healthcare

Physicians employ various methods, including pattern recognition and IDR, to interpret ECGs for diagnosing heart diseases, e.g., heart attacks, but certain conditions, including acute coronary occlusion, pose challenges in diagnosis (Bruno et al., 2023). In such cases, physicians integrate AI with traditional approaches to enhance accuracy and effectiveness in diagnosis (Gupta et al., 2024). The scientific community injected a gelatin and lead oxide solution into a heart specimen donated by the deceased patient’s family. After cooling, they performed a detailed 3D reconstruction of the heart using a spiral CT scanner (Figure 4), achieving a remarkable spatial resolution of 0.3574mm x 0.3574mm x 0.33mm (Deng et al., 2012).

Figure 4

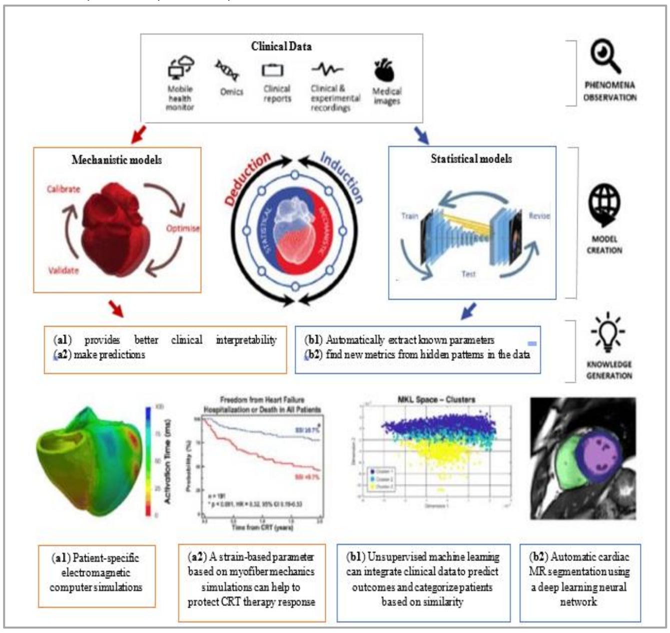
3D Heart models of a single patient dataset based on different sizes. The adult-sized heart was developed from a CT scan. It was then scaled by a multiplying factor of 0.8 for the teenager heart and 0.55 for the infant heart. a. Adult. b. Teenager. c. Infant.



Integrating 3D digital twinning with XR and AI transforms cardiac care (Attaran & Celik, 2023). It aids in simulating procedures, detecting defects like ventricular septal defects, ensuring precise ECG electrode placement, monitoring heart rate via facial feature analysis during surgery, and aiding in the early detection of heart attacks (Rudnicka et al., 2024). Precision cardiology utilizes a digital twin, merging inductive (statistical modeling for predictions) and deductive (mechanistic modeling for simulations). Examples of mechanistic modeling include the Navier-Stokes equation for coronary blood flow, and statistical modeling includes Gaussian processes for heart rate variability (Corral-Acero et al.,2020).

Figure 5

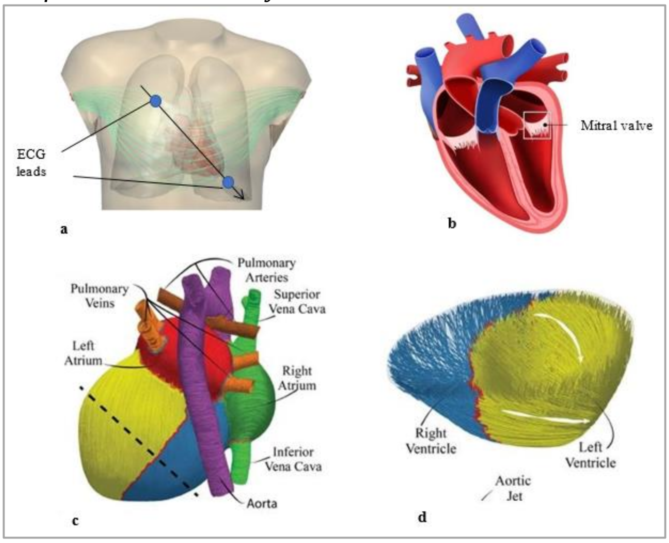
The mechanistic and statistical models of the digital twin, illustrating its construction and four examples of use: a1, [10] a2, [11] b1, [12] b2[13]



A range of software tools, including Materialize Mimics Innovation Suite MIS 22.0, Materialize 3-matic 14.0 (Lau & Sun, 2022), MeshMixer, Rhinocad, MeshLab, Blender, along with techniques like Material Jetting and Boolean operations, facilitated the creation and manipulation of diverse 3D virtual heart models (Figure 5) (Hopfner et al., 2021). The heart digital twin, embedded in a virtual human torso, was constructed via anatomical twinning using MRI scans from 12 patients in 4 hours and fine-tuned through functional twinning with forward Saltelli sampling to replicate real 12-lead ECG patterns, and it accurately represents blood flow and electrical activity (Figure 6). The left atrium receives oxygenated blood from pulmonary veins and is linked to the left ventricle via the mitral valve (Whiteman et al., 2019). The left ventricle pumps blood via the aorta, operating the aortic valve's three leaflets. On the right side, the right atrium collects deoxygenated blood from the vena cava and connects to the right ventricle through the tricuspid valve. The right ventricle propels blood through the pulmonary valve to the pulmonary artery. Electrical signals on the skin surface are tracked to generate synthetic ECGs. Advanced Nvidia V100 and A100 devices power these simulations (Viola et al., 2023).

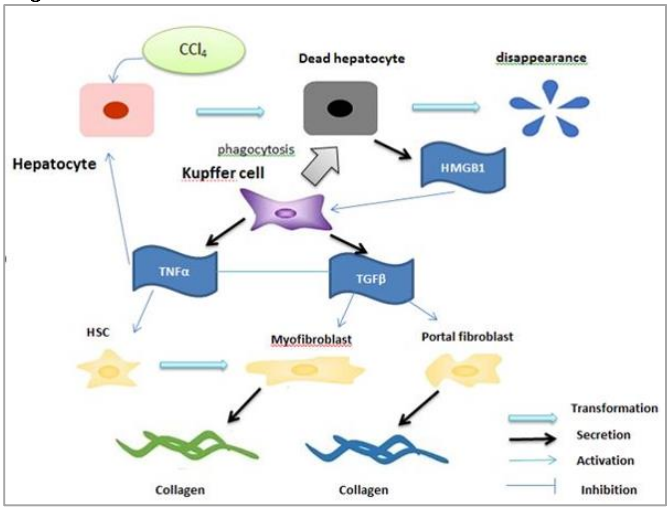
Figure 6

Topological and geometrical features of the cardiac digital twin. ***a.*** *Location of the heart model in a human torso and position of two virtual electrodes with which the ECG is computed.* ***b.*** *Geometrical assembly of the heart model with the main elements, including arteries and veins.* ***c.*** *Zonal separation of the heart with the external fibers orientation; the black dashed line is the trace of the cutting plane of panel d. The passive and active mechanical properties of the tissues are specific to each heart structure.* ***d.*** *Plane section through the apical region of the ventricles to show the orientation of the fibers across the myocardium thickness.*



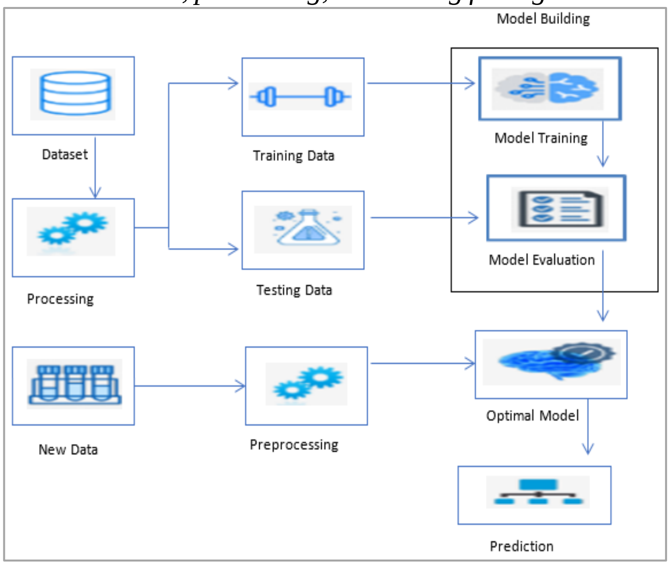
A novel hepatitis classifier utilizing artificial neural networks predicts liver disease (hepatitis) infection levels, aiming for early detection to prevent critical stages. Model evaluation, employing F1 score metrics, revealed the ANN-based model's exceptional accuracy of 0.98-0.99, surpassing traditional models (Palaniappan & Surendran, 2022). Chronic liver inflammation activates hepatic stellate cells, which transform into myofibroblasts and produce extracellular matrix. Excessive extracellular matrix production leads to liver fibrosis, causing scarring that disrupts normal liver structure (Tanwar et al., 2020). The liver fibrosis agent-based model, using hexagonal units, accurately simulated CCl4-induced injury and inflammation (Figure 7). This cascade activated Kupffer cells, recruited monocytes, and triggered hepatic stellate cell activation, leading to fibrosis (Dutta-Moscato et al., 2014). Myofibroblast- and portal fibroblast-derived collagens were modeled separately. Toxic compounds caused them to accumulate in central venous and portal areas, respectively, bridging central regions and spreading throughout the liver, disrupting its structure (Yoshizawa et al., 2022). The model effectively showed fibrosis spread and increased liver stiffness, consistent with histological observations from in vivo experiments (Dutta-Moscato et al.,2014). Sensory analysis revealed two factors involved in fibrosis production and progression, including dead hepatocytes and the ratio of residential liver cells (Yoshizawa et al., 2022).

Figure 7
Digital twin in healthcare



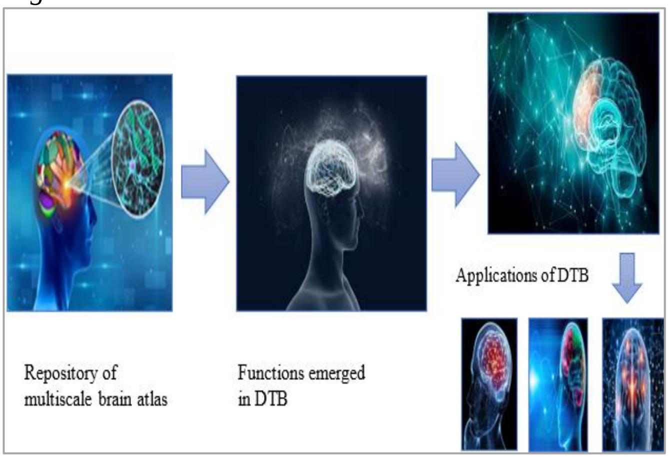
A personalized nutrition program utilizing digital twins was implemented for patients with type 2 diabetes (Chu et al., 2023) and non-alcoholic fatty liver disease (Joshi et al., 2023). After 3 months, the digital twin group exhibited a reduction in Hemoglobin A1c levels from 8.8% to 6.9%, and average weight decreased from 79 kg to 74.2 kg (Shamanna et al., 2020). At the 1-year mark, this group experienced a 2.9-point decrease in Hemoglobin A1c levels, a 2.5-point reduction in liver fat scores, and 72.7% achieved diabetes remission, compared to minimal improvements in the standard care group (Joshi et al., 2023).

Figure 8
Data collection, processing, and testing for digital twins.



A digital twin brain model is proposed, constructed with a multimodal, multiscale brain atlas to mirror biological brain heterogeneity. Trained with biological data using new algorithms, it generates human-like functional signals (Figure 9). Testing in various applications refines its performance, making it applicable to understanding intelligence emergence, studying neurological disorders, and assessing the impact of external stimuli to alleviate attacks. This is a "learn by doing" approach (Xiong et al., 2023). A digital twin brain (DTB) platform simulates an entire human brain with 86 billion neurons (Feng et al.,2024), seamlessly connected to a mouse body model via Rosbridge software. Utilizing the Fugaku supercomputer and GPU clusters, it models key brain regions (Kuniyoshi et al., 2023): the secondary motor cortex (M2) generates rhythmic signals for movement using 100 central pattern generators (CPGs) including Matsuoka oscillator (Sharma et al., 2016) and Leaky Integrate-and-Fire (LIF) models; the cortico-basal-ganglia-thalamus (CBT) processes these signals and sends motor commands to mouse body (Kuniyoshi et al., 2023); and the cerebellum (CB) fine-tunes these commands based on learning (Anderson et al., 1993). The LIF model in M2 and various brain regions simulates neural firing dynamics crucial for generating rhythmic patterns and processing sensory inputs (Teeter et al., 2018). Neural activity is converted into Blood-Oxygen-Level-Dependent (BOLD) signals for fMRI detection (Zhang et al., 2019), with synaptic parameters fine-tuned using the Hierarchical Mesoscale Data Assimilation (HMDA) method. The DTB accurately replicates real brain signals at rest and during visual tasks, achieving high correlations and outperforming existing simulations with real-time factors of 65, 78.8, and 118.8 for different firing rates (Feng et al., 2024).

Figure 9
Digital twin in brain model.



Digital Transformation in Cancer Research

Susilo et al. 2023 used digital twin technology to simulate personalized mosunetuzumab dosages for non-Hodgkin lymphoma patients by crafting individual models and forming a virtual population (VPOP). Testing diverse dosage plans on these VPOPs identified tailored treatment strategies, predicting successful therapy options for each individual (Susilo et al., 2023). Digital twins, machine learning, and natural language processing revolutionize cancer progression monitoring.

Trained on 714,000 reports, these models, using patient histories, surpass single-report analysis in predicting metastatic diseases with precision (Batch et al., 2022). The scientific community believes that CPDT integrates advanced tech, revealing immune factors' impact on metastatic lung cancer. Key cells like macrophages and dendritic cells determine personalized treatment, shedding light on immune defense and cancer cell evasion (Rocha et al., 2023). Meraghni et al. (2021) used thermographic fusion in a digital twin model for early breast cancer detection, analyzing temperature changes in breast tissues with simulated heat transfer data. Smart devices offer real-time updates, considering both thermal and additional factors, enhancing detection beyond temperature changes alone (Meraghni et al., 2021). Mourtzis et al. (2021) reported Quantx, a tool for quantitative insights to enhance the pace and accuracy of breast cancer detection (Mourtzis et al., 2021). Kaul et al. (2023) reported a digital twin-based clinical support system for prostate cancer, accurately forecasting cancer progression, and results enabled clinicians to make precise treatment decisions based on biopsy data (Kaul et al., 2023). The SDTC initiative establishes patient-specific digital twin models, integrating molecular, phenotypic, and environmental factors. Employing computational treatment with multiple drugs enhances precision medicine, tailoring treatments for optimal effectiveness (Bjornsson et al., 2020).

A digital twin framework with multiple mathematical models is suggested for addressing disease dynamics and research question analysis as the simplified cancer cell count model (x'prol(t)=r.xprol(t)) lacked specifics on drug and immune responses, indicating the necessity for more detailed models, particularly for complex procedures like radiology and surgery (Sager et al.,2023). Researchers employed a Gompertz growth model in mathematical simulations to explore the Norton-Simon hypothesis, considering that cancer cell growth slows as tumors enlarge. This investigation revealed the potential effectiveness of aggressive chemotherapy for breast cancer patients (Sager, 2023).

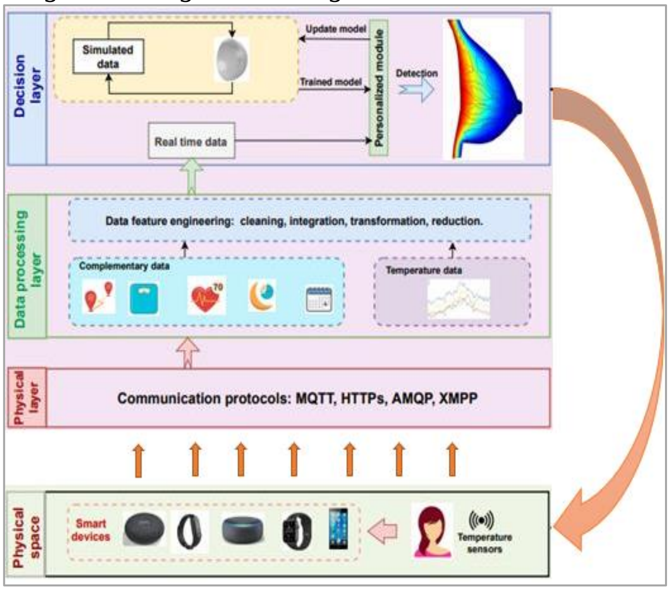
Digital twin's role in Precision Medicine and Drug Design

Bayer has been active in computer simulation technology for more than 20 years. Bayer utilized computer simulations in the anticoagulant field to identify the most efficient dosage for treatment. This approach resulted in patients experiencing fewer strokes, thrombosis, and fewer side effects. Consequently, patients experience fewer strokes, thrombosis, and fewer side effects. Bayer Launches Precision Health Unit for Digital Innovation. In 2022, it also invested 9.5 million dollars in Woebot Health, an AI-powered behavioral healthcare platform. Additionally, in 2020, the G4A Digital Health Partnership Program was also launched by Bayer to foster digital collaborations in cardiometabolism, oncology, and women's health. Canadian imaging company Altis is leading a project with AstraZeneca and Bayer to advance healthcare research using digital twins. Altis Labs, backed by $6 million in seed funding as of June, contributes its Nota imaging platform, renowned for its real-world cancer imaging database for AI research.

Digital twins in cancer Diagnosis

Breast cancer is one of the most prevalent cancers (Arnold et al., 2022), and early detection can significantly improve survival rates (Seely, 2023). Thermography, a painless and non-invasive technique, detects breast cancer early by analyzing heat map profiles of the breasts; skin above tumors typically shows higher temperatures than nearby tissues (Mashekova et al., 2022). Computer-aided detection is used to analyze abnormalities in thermograms for enhanced effectiveness in breast analysis (Raghavendra et al., 2019). However, human physiology, breast size, and geometry vary widely, making a universal normal temperature threshold unreliable for accurate diagnosis. Each person's normal temperature differs based on individual physiology (Geneva et al., 2019). Therefore, a personalized medicine approach is crucial for precise breast cancer diagnosis (Vallee et al., 2024). Combining thermography with digital twin technology can enhance diagnostic accuracy, supporting personalized healthcare strategies. Human digital twins integrate real health data and predict breast cancer detection through a layered middleware approach. In the physical space, IoT technologies (Meraghni et al., 2021) like smart wearable devices with thermal sensors (e.g., a flexible card design with 28 mini biosensors, a brassiere with 12-20 Nickel Manganate-based NTC chip thermal probes per breast, a wearable brassiere with 8 LM35 sensors, and a wearable breast patch with 8 ADT7420 sensors) collect real health thermal data (Ketfi et al., 2024). The physical layer uses Machine-to-Machine stack protocols (HTTPS, CoAP, MQTT, MQTT-SN) to enable communication with the digital network for data transfer from thermal sensors (Durkop et al.,2015). In the data processing layer, the data is transformed to a standardized format, cleaned, and reduced to be prepared for algorithmic analysis. The decision layer employs offline-trained digital twin models with simulated data to detect breast cancer patterns. In the online phase, real-time patient data is monitored for deviations, with predictions adapted through personalized modules for accurate diagnosis (Meraghni et al., 2021).

Figure 10
Diagnosis in digital twinning.

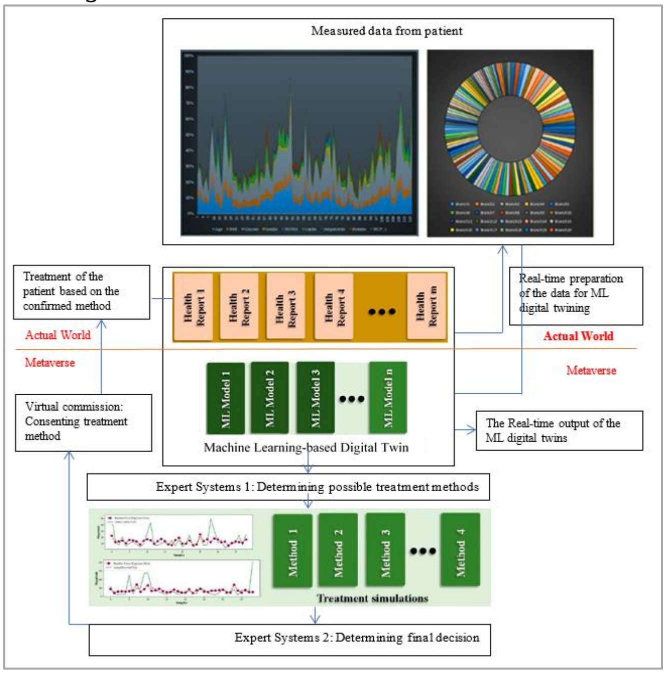


Lung cancer is the most frequently diagnosed cancer worldwide, as reported in 2022 (Bray et al.,2022). In Pakistan, it is the second most common cancer in men and the third most common in both genders (Sheikh et al., 2022). Lung cancer patients have a higher risk of developing pulmonary embolism (PE), with an incidence rate of about 3.7% (Li et al., 2018). This leads to increased mortality rates due to the frequent misdiagnosis or late diagnosis of PE (Dong, et al., 2023). Integrating digital twin technology with machine learning and deep learning algorithms, including convolutional neural networks (CNN), enhances the accuracy and early detection of lung cancer-related conditions, including pulmonary embolism (PE) and deep vein thrombosis (DVT) (Moztarzadeh, et al., 2023). A lung cancer digital twin has been developed (Stahlberg, et al., 2022) to diagnose these conditions by incorporating real patient data from hospitals in Qujing, Kunming, and Chongqing, combined with physics-based rendering and CNN for precise diagnostic analysis (Zhang, et al., 2020). The clinical data recorded comprise age, gender, risk factors, D-dimer level, ECG results, cancer type and location, leukocyte count, TNM stage, and thoracic CT findings (Zhang & Tai, 2022). The physics-based rendering process involves a visual pipeline using 2D CT scans to create a mesh (Zhang, et al., 2020), which Unity software then transforms into an interactive 3D environment. This software supports multiple programming languages, including Python and C#, and operates on platforms like Android, iOS, PC, and web browsers (Hussain et al., 2020). Healthcare professionals utilize the Pico G2 VR headset to visualize and interact with patients in 3D space (Zhang & Tai, 2022). The deep learning algorithm employs a custom convolutional neural network (CNN)(Chithra & Bhavani, 2024) with nearest neighbor data imputation technique to fill gaps in medical data (Pujianto et al., 2019). This CNN architecture effectively learns complex patterns and relationships within medical data, enabling accurate predictions for pulmonary embolism (PE) and deep vein thrombosis (DVT) in lung cancer patients (Zhang et al.,2020).

An AI-based digital twin technology named "vPatho" was established to diagnose and grade prostate cancer (Eminaga et al., 2024) by utilizing two neural networking models, including RUS-Wg-MSResNet and XGBOD (Ge et al., 2023). It was evaluated using various metrics, including Cohen’s Kappa and AUROC, focusing on different aspects of prostate cancer tissue and morphologies (Abraham & Nair, 2019). Cohen's Kappa scored 0.8385, indicating substantial agreement between vPatho and human pathologists, while AUROC scored 0.955, demonstrating high accuracy in differentiating between cancerous and non-cancerous cells (Nagpal et al., 2020). Pathol performed well on both old (over 20 years) and new tissue samples for diagnosing prostate cancer (Eminaga et al., 2024). Pathol accurately classified 99% of whole mount slides by the utilization of ResNet-34 (Pinckaers et al., 2021). Prostate cancer metastasis in lymph nodes was diagnosed by an AI tool ProCalNMD, which achieved an AUROC score of 0.975 to 0.992, with sensitivity over 95.5% and specificity above 92.1%. The tool identified 4.3% of cancerous slides missed by pathologists and showed superior diagnostic sensitivity (Wu et al., 2024). Overall, vPatho and ProCalNMd proved to be highly accurate and reliable tools, comparable to human pathologists. They can aid oncologists by potentially speeding up clinical workflows and improving prostate cancer diagnosis, with their findings integrated into electronic pathology reports (Eminaga et al., 2024) (Wu et al., 2024).

A cancer patient digital twin framework was proposed, which integrated various Machine learning models in the metaverse, including ML linear regression, decision tree regression, random forest regression, and gradient boosting algorithms to revolutionize the diagnosis and treatment of cancer, specifically breast cancer (Moztarzadeh et al., 2023) (Figure 11). Three digital twin types—Grey Box, Surrogate, and Black Box—were proposed for cancer diagnosis, including pediatric cases. The Black Box digital twin, utilizing deep learning, emerged as the most advanced, offering predictive insights from individual patient pattern analysis (Wickramasinghe et al., 2021). Digital twin technology, with machine learning, predicts neurological risks in pediatric cancer treatment. Integrating digital twinning with compassionate use data boosts cancer research by expanding available data for analysis (Thiong’o & Rutka, 2022).

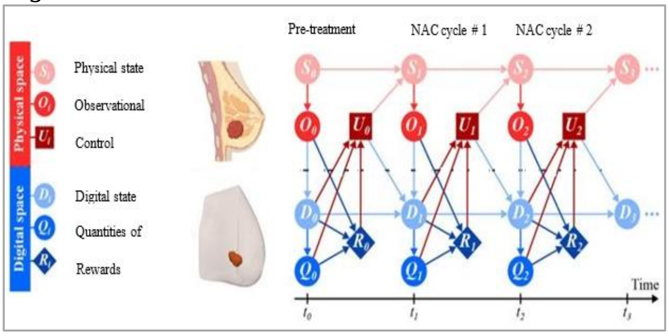
Figure 11
Digital twining for cancer patients using machine learning.



AI-based endometrial cancer patient digital twin can integrate and represent complex relevant clinical genomic information, which is then utilized by AI algorithms that determine cancer diagnosis prediction, overall survival rate of the patient, and behavior of disease over its lifecycle by considering risk factors. A case study focused on developing a digital twin for endometrial cancer, coupled with AI, aiming to integrate extensive data related to endometrial cancer, providing valuable insights for diagnosis, prognosis, and treatment monitoring. It also represents and understands complex factors associated with endometrial cancer (Kaul et al., 2023). Exploring digital twins for biomarker monitoring, such as specific metabolites detected through breath analysis, holds promise for early cancer detection. Integration with machine learning algorithms enables predictive modeling of cancer development (Lueno et al., 2022).

Digital twins in Cancer treatment
Simulations through digital twins facilitate the exploration and determination of diverse treatment options, enabling healthcare professionals to discuss choices with patients. This approach contributes to overall enhance patient care and satisfaction in cancer treatment (Kaul et al., 2023). Digital twins enhance precision radiotherapy (intelligent radiotherapy) by predicting accurate dosage, foreseeing radiation delivery to vital organs, allowing needed adjustments, and ensuring precise patient positioning to target tumors. Radiomics complements digital twins by extracting detailed information from tumor imaging in healthcare (Chen et al., 2022). Digital twins, employing biomechanistic models, enhance cancer management by predicting individual patient outcomes and guiding treatment decisions, such as monitoring breast cancer response to neoadjuvant chemotherapy and facilitating tumor growth studies (Lorenzo et al., 2023).

Figure 12
Digital twins in cancer treatment.



A personalized digital twin utilizing customized mathematical models can provide tailored phlebotomy schedules for Polycythemia vera patients, refining accuracy with each measurement to align with patient preferences (Sager, 2023).

Revolutionizing: Human Digital Twin Concept
Augmented digital twin serves as the foundation for the human digital twin model. The human digital twin comprises a physical entity and its virtual counterpart in cyberspace with two-way communication. Additionally, it integrates surroundings and entities in the physical space along with the virtual surroundings and interactions with other digital twins (Shengli & Update, 2021). A complete patient digital twin for clinical trials is distant due to limited knowledge. However, specific organs and processes digital twins, like brain tissues, diabetes & heart models, are in use for complex procedures and predicting insulin dosage, showing promise for future medical advancements.

Digital Mirrors: The Art and Science of Digital Twin Construction
IoT smart devices efficiently collect diverse health data, including age, weight, height, blood pressure, and electrocardiogram (ECG). This comprehensive dataset is then transmitted to a Sink Centre for further processing (Shengli & Update, 2021).

3D Deep Convolutional Generative Adversarial Network (DCGAN) algorithms predict vertebral fracture risk during metastatic cancer surgery, generating detailed trabecular vertebral bone structures (Ahmadian et al., 2022). CT scan data can be transformed into refined 3D models by leveraging software such as Mimics v17, 3-Matic 9.0, and CATIA V5 (He et al.,2021). Trabecular microstructure integrates into the patient's vertebra via FE-based optimization, ensuring a seamless transition. The model is refined for precise FE simulation, predicting vertebral fractures under compression and flexion. DCGAN employs hyperbolic and symbolic functions for enhanced imaging and classification (Ahmadian et al., 2022). For accurate simulations of lumbar spine behavior, the lower L5 was fixed, employing special joint mimicry elements. Two simulations were executed: one with a 7.5Nm force on L2 for bending, tilting, and stretching and another with a steady 400N force on L2 while managing inter-vertebral angles. These simulations yielded valuable insights into spine reactions and intervertebral movements (He et al., 2021). To simulate vertebroplasty on a 3D fractured vertebra, a continuum damage model with ReconGAN is employed to create the model. Combining Navier-Stokes and a governing equation with a level-set method evaluates Φ to track the interface between bone marrow and injected cement, assuming a thickness value of e = hmax/2 as follows:

$\partial\Phi/\partial t + \mathbf{u}.\nabla\Phi = \gamma\nabla.\ (\varepsilon\nabla\Phi\text{-}\Phi\ (1\text{-}\Phi\ )\ \nabla\Phi/|\Phi|)$ (Ahmadian et al., 2022).

Kinzl, Wijayathunga, and Chevalier validated computer-simulated models for augmented vertebral bones. Kinzl's 41 models closely matched real bone tests, while Wijayathunga's 11 models overestimated augmented bone strength. Chevalier identified the most effective augmentation with compliant cement for superior reinforcement and stability (Badilatti et al., 2015).

A proposed method for constructing a collaborative digital twin of endometrial cancer patients involves preprocessing data through cleaning, filtering, handling missing values, and balancing data. Machine learning algorithms, including clustering, deep learning, and regression, are employed to characterize the model and facilitate the diagnosis of endometrial cancer (Kaul et al., 2023). The concluding step in collaborative digital twin modeling requires rigorous quality assurance by domain experts. Continuous upgrading of the digital twin model with the data from the real world is essential to enhance its performance (Ellahham et al., 2020).

CONCLUSION

By using the DTs technology health care platforms are enabled to analyze and interpret huge amount of patient's data and design precise models of cancer progression to accurately distinguish between diseased and healthy individuals. Therefore, by utilizing a reliable dataset, several ML- based approaches for breast cancer were simulated and replicated to illustrate the feasibility and simplicity of the digital twinning procedure. This strategy allows modelling cancer diagnosis, progression over time and predicting future behavior. It can also be tremendously valuable in developing new therapies and treatments, as well as identifying potential complications before their occurrence. However, it's important to note that instead of its benefits, there are some limitations in utilizing the ML- based digital twining in healthcare systems. For example, the chances of biasedness in data and models, the difficulties in interpreting the results of non-experts and the requirement of large amount of data to train the models. However, considering these restrictions, proposed platforms can revolutionize the treatment and diagnosis of cancer.

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