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Article

Application of Industry 4.0 and digital twin in the field of smart healthcare

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Abstract: There is an increasing need for preventive health care as well as precise diagnosis and tailored treatment of different diseases in recent years. Providing customized treatment for each patient and maximizing accuracy and efficiency are main goals of a good healthcare system. This thesis explores the integration of digital twin technology with Industry 4.0 in healthcare. Digital twins create virtual representations of physical systems, enabling real-time monitoring and tailored treatments. Key elements include the living human body, IoT, digital twin, cloud computing, and simulation. The architecture comprises data acquisition, data munging, data storage, data simulation with analytics, and user access layers. Creating a digital twin involves precise 3D modeling, representing the entire body or specific organs. A case study demonstrates real-time monitoring using wearable sensors for blood pressure, blood sugar, and heart rate. Data is transmitted, integrated with the digital twin, and accessible via a website with alarms for abnormal readings. While Industry 4.0 and digital twin adoption in healthcare is evolving, the architecture serves as a reference. It offers real-time data for diagnosis and treatment, with potential for advanced simulations. Challenges include automated data systems and privacy concerns. Despite limitations, this integration holds promise for precision medicine and personalized healthcare.

Keywords: Industry 4.0; digital twin; IOT; precision medicine; healthcare; big data

1. Introduction

A A digital twin is a virtual representation of a physical system, process, or product, serving as a bridge between the physical and digital realms. It is integrated into Industry 4.0 through the utilization of sensors to gather real-time data from its physical counterpart [1]. This data is then employed to create simulations, utilizing various analytical techniques, software programming, and modeling, to understand its behavior in real-world scenarios. Several case studies have been conducted, employing different scenarios and varying parameters, aiding researchers, engineers, scientists, and medical professionals in making informed decisions. Digital twins are also referred to as virtual twins, virtual prototypes, or digital asset management [2–4]. The inception of a digital twin involves its creation by specialists to draw conclusions and enhance decision-making. These digital counterparts receive input from IoT-based sensors, which collect data from their physical counterparts, enabling real-time simulation. This process facilitates insights into potential issues and can serve as a virtual prototype before physical production. Digital twin technology finds applications in various industries such as manufacturing, agriculture, and aerospace engineering, aiming to enhance system efficiency, reliability, and fault detection [5–7]. Recently, developed countries have started implementing digital twin technology alongside Industry 4.0 in healthcare and medical science [8]. This convergence of Industry 4.0 and digital twins is being widely adopted across various domains. Traditional drug therapy faces limitations such as medication ineffectiveness, and personalized medicine has gained prominence in healthcare [9–11]. Precision medicine, which considers genetic, environmental, and lifestyle factors, has garnered attention, and digital technology has been used to construct virtual physiological models for clinical applications [12–14]. Advancements in big data, cloud computing, virtual reality, and the Internet of Things (IoT) have paved the way for digital twin applications in healthcare. Digital twins are evolving into virtual replicas of human organs, tissues, cells, or microenvironments, continuously adapting to real-time data and predicting future states, including defects and failures. They optimize processes through closed-loop interactions with their surroundings [15–17]. Digital twins encompass two categories of technologies: statistical models driven by data and mechanical models integrating multi-scale knowledge and data. Numerical models calculate structural performance, while AI models trained with samples and data provide real-time insights from sensors [18,19]. Digital twins have revolutionized various industries, enhancing efficiency and problem detection [20]. Healthcare is an emerging domain where digital twins can have a significant impact [21]. In healthcare, digital twins can treat patients as virtualized assets, enabling their utilization in diverse healthcare scenarios [22,23]. This review explores the progress and potential applications of digital twin technology in medicine, highlighting its future opportunities and existing challenges in digital healthcare. Industry 4.0 aims to advance medical technology by integrating physical systems with the Internet of Things (IoT), cyber-physical systems (CPSs), big data, and cloud computing [24–26]. The incorporation of digital twins into this framework creates a robust platform for real-time parameter monitoring, enabling intelligent decision-making through simulation and modeling [27]. This paper discusses the architecture and integration of digital twins with Industry 4.0, providing insights through a patient case study, demonstrating its potential to benefit humanity through continued evolution and advancement.

2. Materials and method

Digital twin technology key elements and architecture will be studied in detail along with the integration of digital twin with Industry 4.0. The making of the digital twin procedure is also discussed with architecture. The application of Industry 4.0 with digital twin is tested on a human being and a model case study was presented and tested its work in the real case application.

3. Key elements of Industry 4.0 and digital twin for health care

The key elements of Industry 4.0 and the digital twin structure are fundamental in creating a dynamic and responsive environment known as smart healthcare. These elements interact harmoniously with physical systems and the living human body, particularly patients, to enable real-time monitoring and tailored treatments, even in emergency situations.

Living human body (patient): The central component of this framework is the human being, often a patient, whose health conditions require continuous monitoring and potential intervention. This can involve individuals in need of ongoing care or those who have previously undergone treatments and need real-time monitoring to generate alerts in case of emergencies.

Internet of things (IoT): IoT extends internet connectivity to a wide range of devices, including sensors, laptops, computers, tablets, mobile phones, and more. These devices are distributed globally and communicate with users and physical systems, enabling remote monitoring and informed decision-making [28].

Digital twin: The digital twin represents a virtual replica of the patient, allowing for comprehensive monitoring of their health condition. Additionally, various digital twin representations of different body parts are created in the cyber space to facilitate simulations and support decision-making processes. These digital twins are constructed according to established procedures.

Cloud computing: Cloud computing is the backbone of this ecosystem, offering shared pools of configurable computer systems that can be rapidly accessed over the Internet. Cloud computing relies on resource sharing to achieve coherence and cost-effectiveness, much like a public utility. Doctors, researchers, and healthcare professionals use cloud computing resources to conduct simulations, leveraging various software, analytics, and modeling tools to make informed decisions regarding patient treatment.

Digital twin technology goes beyond healthcare and extends into other domains such as personalized medicine, precision public health, and smart medicine manufacturing. It has the potential to revolutionize the healthcare sector by providing a platform for real-time monitoring and data-driven decision-making, ultimately improving patient outcomes and the efficiency of healthcare delivery.

In summary, the integration of these key elements—the living human body, IoT, digital twin, cloud computing, and simulation—forms the foundation of Smart Healthcare, enabling proactive monitoring and personalized treatments for patients while also contributing to advancements in medical research and healthcare manufacturing processes.

4. Basic architecture of Industry 4.0 and digital twin structure

The architecture of Industry 4.0 integrated with digital twin comprises five essential layers, each tailored and customized to meet the specific requirements of healthcare and treatment applications:

Data acquisition layer: This foundational layer involves the collection of data from various sources, primarily through IoT-based sensors that are integrated with the physical human being (typically the patient). These sensors gather real-time data on the patient's health status and transmit it to a central cloud server for processing and analysis.

Data munging layer: Once the data is acquired, it is passed to the data munging layer. Here, data preprocessing and transformation tasks take place. Data cleaning, normalization, and formatting ensure that the data is in a suitable state for further analysis. This layer plays a crucial role in preparing the data for meaningful insights [29].

Data storage layer: Data storage and management are handled by this layer. Specialized data warehousing systems are employed to store the collected data. Backup and disaster recovery systems are also integrated to ensure data integrity and availability [30].

Data simulation with analytics layer: In this layer, data analysis is performed to derive valuable insights. Algorithms and software programs are applied to the preprocessed data to generate simulations, conduct analytics, and develop predictive models. Human intervention may also play a role in interpreting the results and making informed decisions based on the analysis [29].

User access layer: The user access layer serves as the interface through which authorized users can interact with the system. To ensure data protection and privacy, users are required to authenticate themselves using a user ID and password. This layer enables healthcare professionals, researchers, and relevant stakeholders to access and utilize the data for monitoring, analysis, and decision-making purposes [30].

This integrated architecture eliminates the need for manual data collection systems and facilitates real-time data acquisition and analysis. It ensures data integrity, security, and accessibility while enabling healthcare professionals to make informed decisions based on the insights derived from the digital twin and Industry 4.0 technologies.

5. Making of digital twin for health care

The process of creating a digital twin is depicted in **Figure 1**, involving the use of AutoCAD and 3D modeling techniques. This procedure commences with the acquisition of precise dimensions from the physical object being replicated. The design is then meticulously crafted, and a virtual prototype is developed. This virtual representation is subsequently crosschecked against the actual physical object to ensure accuracy and fidelity.

Digital twins can be constructed for various purposes, encompassing the entire human body or specific body parts such as the heart, kidneys, liver, and more. These digital twins serve as a foundation for analysis and simulation. For instance, simulating the behavior of the heart involves employing fluid dynamics to study blood flow patterns, gauge the cardiac system's ability to withstand pressure, and monitor blood flow within veins and arteries while accounting for potential restrictions.

The advent of digital twin technology holds immense promise for the future of precision medicine. Already, it has found applications in the medical field, contributing to disease prediction through physical examination and enhancing the accuracy of medical diagnostics [31]. By leveraging digital twins, healthcare professionals can gain deeper insights into the human body's complexities and variability, ultimately paving the way for more personalized and effective medical treatments and interventions.

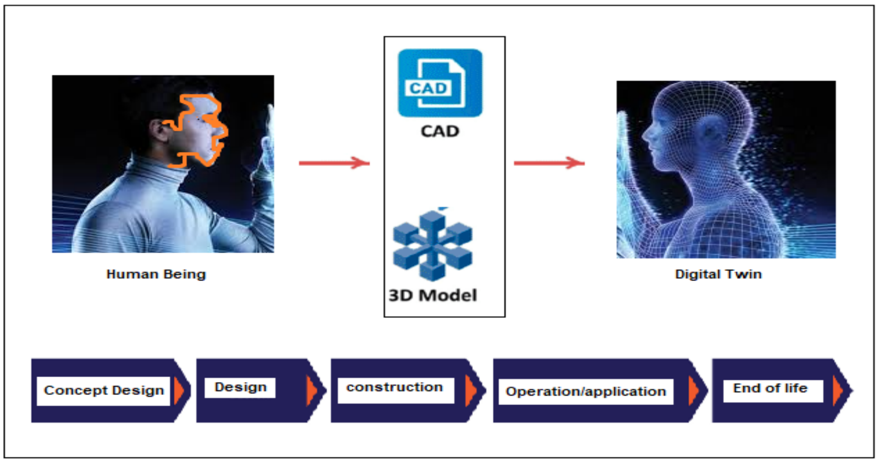

Figure 1. Digital twin for health care.

6. Integration of digital twin with Industry 4.0 for health care

Once the digital twin is created following established procedures, it is securely stored in the cyber space with a unique identifier assigned to the specific patient for whom the digital twin has been generated. All relevant patient information, including a detailed health history, is stored in the same dedicated folder associated with the patient's digital twin. This comprehensive repository ensures that both the digital twin and the patient's health data are readily accessible and well-organized for healthcare management. To gather the necessary data for monitoring and analysis, IoT-based sensors are strategically placed within the human body, as illustrated in **Figure 2**. These sensors continuously collect data and employ wireless technology to transmit this data to a cloud-based server. The collected data is stored in the cloud within the designated patient folder, where it is seamlessly integrated with the patient's digital twin. Utilizing various software programming tools and algorithms as given in **Table 1**, simulations are performed, incorporating data analytics and mathematical modeling. This process enables the system to generate meaningful insights and predictions about the patient's health status. Moreover, the collected data can be visualized by authorized users at any time, facilitating observation and in-depth analysis. An alarm system is integrated with the collected data, configured to trigger alerts based on predefined parameters. When specific health metrics or conditions deviate from acceptable ranges, the system sends alarms to the user. These alarms prompt immediate attention and action. Users can access the system securely using a unique user ID and password through various devices such as mobile phones, laptops, and desktop computers. This accessibility ensures that users can promptly respond to alarms and make informed decisions based on real- time data and system-generated alerts.

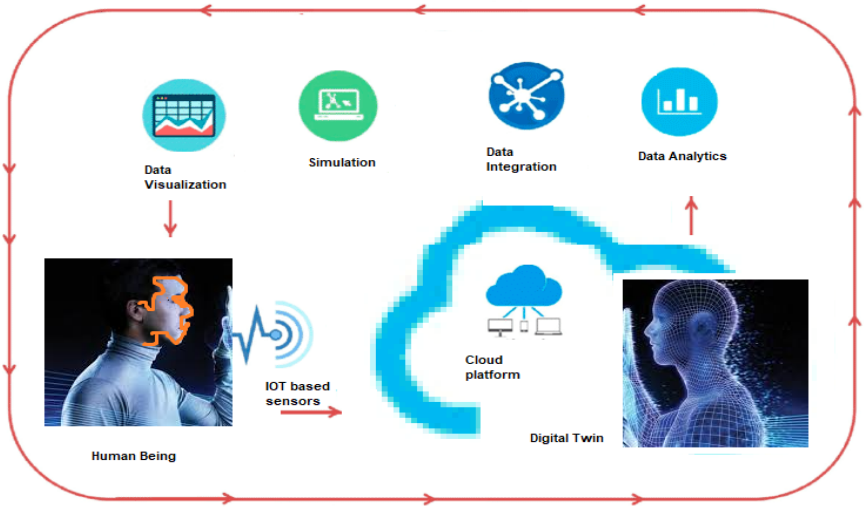

Figure 2. Integration of digital twin with Industry 4.0 for health care.

Table 1. Software programming tools.

Sl. No.	Software programming	Specific use for health and disease analysis	Software Application reference in earlier research
1	MATLAB	Data analysis and visualization	[32–34]
2	Python	Statistical analysis and machine learning	[35,36]
3	R	Data mining and predictive modeling	[37,38]
4	SPSS	Statistical analysis and regression analysis	[39]

The system described here serves a dual purpose, enabling both preventive and corrective healthcare measures. It supports ongoing monitoring for patients who have previously undergone treatments or surgeries, ensuring their health is continually checked in real-time. Additionally, it provides a valuable tool for preventive healthcare, offering proactive monitoring and early intervention to maintain and improve patients' overall well-being.

7. Case study on implementation of Industry 4.0 and digital twin

In the contemporary landscape of healthcare, the integration of cutting-edge technologies has become paramount in enhancing patient care and outcomes. This case study delves into the practical application of Industry 4.0 principles and digital twin technology in healthcare monitoring, showcasing a tangible example of their transformative potential. Through a real-world scenario, we explore the seamless integration of wearable sensors, advanced data analytics, and digital twin frameworks to revolutionize healthcare monitoring.

Wearable sensors: At the heart of this innovative approach lies a suite of high-precision (99.9%) wearable sensors meticulously designed to capture vital health parameters. Among these, the Huawei make Band 6 model, Fitbit make Charge 4 model is used. Strategically placed on the subject's body, these sensors operate seamlessly, continuously monitoring critical health metrics such as blood pressure, blood sugar levels, and heart rate. With a minimum data logging frequency of every 5 min, they ensure the collection of a rich and comprehensive dataset over extended periods.

Data transmission: The seamless transmission of health data from wearable sensors to a central repository forms the backbone of this monitoring system. Leveraging secure communication protocols such as Bluetooth Low Energy (BLE) or Wi-Fi, the collected data is transmitted wirelessly to a centralized server. This robust data transmission mechanism ensures the efficient and reliable transfer of health data, safeguarding its integrity and accessibility for further analysis and monitoring.

Data analysis and monitoring: Harnessing the power of advanced software algorithms and machine learning techniques, the collected health data undergoes rigorous analysis and monitoring. Platforms such as MATLAB or Python, supplemented by TensorFlow or Scikit-learn libraries, serve as the foundation for sophisticated data analytics. These algorithms provide real-time insights into current health metrics and historical data trends, empowering continuous monitoring and early detection of abnormalities. By employing state-of-the-art analytical tools, healthcare providers gain invaluable insights into patient health status, enabling timely interventions and personalized care strategies.

Data alarms: Central to this monitoring system are customizable alarm thresholds tailored to individual patient profiles and clinical guidelines. When health readings deviate from predefined thresholds depending on the condition of the patient which is variable and set as per doctor's advice, alerts are promptly triggered and transmitted to the user's mobile devices. This proactive approach ensures timely intervention and mitigates potential health risks, enhancing patient safety and well-being.

Data quality assurance: Ensuring the accuracy and reliability of collected health data is paramount to the success of this monitoring system. Rigorous validation processes, including sensor calibration, accuracy checks, and outlier detection algorithms, are meticulously executed. Regular calibration of sensors in every 6 months through the certified labs against reference standards and validation protocols uphold data accuracy and integrity. Furthermore, robust encryption protocols safeguard patient privacy and confidentiality, instilling trust and confidence in the system's data security measures.

Digital twin integration: A hallmark of this innovative approach is the seamless integration of patient health data with digital twin technology. By creating a virtual replica of the patient's physiological state and health conditions, digital twin integration enables real-time monitoring and simulation through a dedicated virtual space. This virtual representation facilitates personalized healthcare interventions, predictive analytics, and scenario-based simulations, empowering healthcare providers with actionable insights and decision-making support.

As demonstrated in **Figure 3**, historical data collected over a day reveals specific health parameter fluctuations. For instance, it highlights instances where the diastolic blood pressure spiked to 142 mm Hg, while the systolic blood pressure dropped to 79 mm Hg. This level of detail enables healthcare providers and patients to closely track health trends and respond to potential health issues promptly.

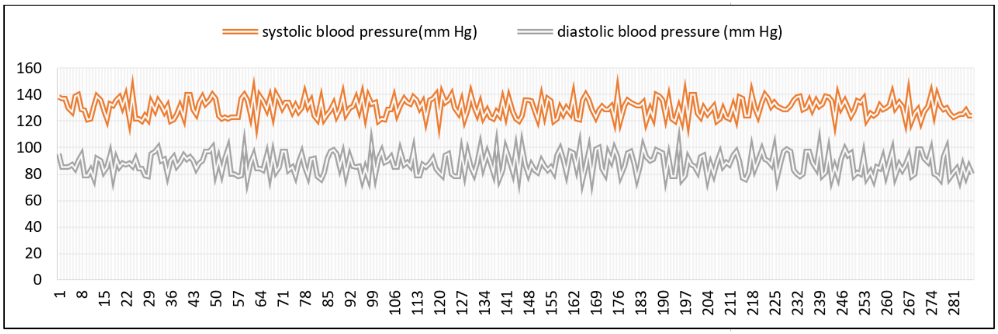

Figure 3. Blood pressure trend data of patent collected online.

Overall, this case study showcases the practical application of Industry 4.0 and digital twin technology in healthcare, offering real-time monitoring, data analysis, and early intervention capabilities to improve patient well-being and healthcare outcomes.

As shown in **Figure 4**, the historical data collected in the system is being crosschecked where it is observed that the blood sugar level has gone up to 200 mg/dL and the blood sugar level has gone down to 122 mg/dL. The data is collected for one day and the frequency for data logging is set for every 5 min.

As shown in **Figure 5**, the historical data collected in the system is being crosschecked where it is observed that the heart beat level has gone up to 105 numbers per minute and the heart beat level has gone down to 81 numbers per minute. The data is collected for one day and the frequency for data logging is set for every 5 min.

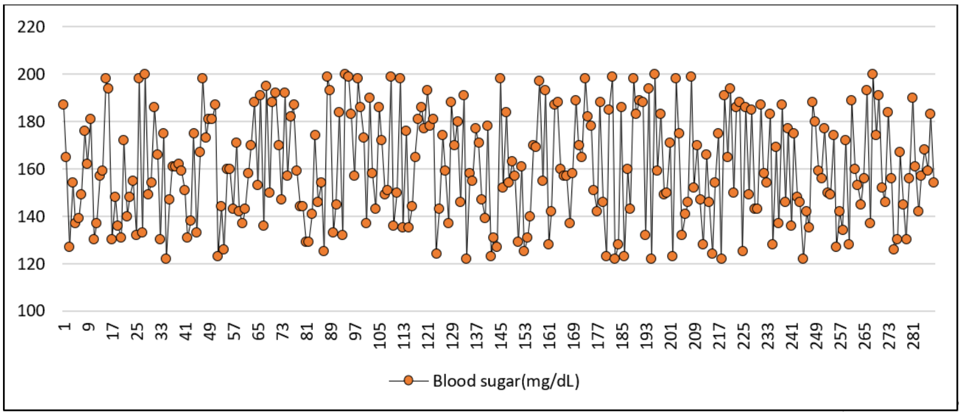

Figure 4. Blood sugar level trend data of patient collected online.

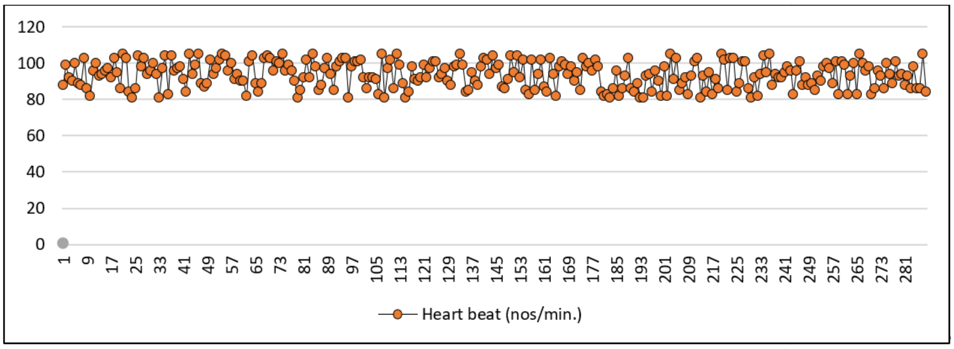

Figure 5. Heart beat trend data of patient collected online.

8. Observation and discussion

From the above study it is clear that the application of Industry 4.0 and digital twin is in the evolving stage in the field of health care. The architecture discussed in the thesis is used for a single case scenario. Different architectures can be developed as per the requirements of the specific case. It will be used as a reference for developing other architectures. The case study conducted on a patient also represents a basic application of the digital twin technology along with Industry 4.0. Different data related to blood pressure, blood sugar level, heart beat has been collected online on a real-time basis from the patent. The alarm is also generated and received by the patient on his mobile phone as per the set value for all the parameters i.e., blood pressure, heart beat and blood sugar. This data can be used by doctors for diagnosis and treatment. This type of data for a prolonged period can be really helpful and used for simulation and drawing inference by using different mathematical and logical algorithms.

9. Limitations

Despite its unique advantages due to the unavailability of real-time biomechanical analysis, it is difficult to analyze without a complete automated data system which needs to be fed manually. Complex digital twin models with high accuracy and flexibility like soft tissues are still a limitation to constructing in 3D modelling. Online data collection on a real-time basis by using sensors without any interruption is still a challenge as human beings and their privacy are involved in this framework.

10. Conclusion

The integration of Industry 4.0 principles and digital twin technology represents a significant advancement in the realm of smart healthcare. By seamlessly blending cutting-edge technologies with traditional healthcare practices, this integration offers a transformative approach to preventive health care, precise diagnosis, and tailored treatment modalities. The amalgamation of wearable sensors, advanced data analytics, and digital twin frameworks enables real-time monitoring, data-driven insights, and proactive interventions, thereby enhancing patient outcomes and elevating the quality of care.

Through the presented case study, it becomes evident that the application of Industry 4.0 and digital twin technology in healthcare is still evolving. While the discussed architecture serves as a foundational framework, its adaptability allows for the development of tailored solutions to address specific healthcare needs. Real-time data collection and alarm generation empower both patients and healthcare providers to monitor health conditions actively and initiate timely interventions, thereby improving patient well-being and healthcare delivery.

However, despite its numerous advantages, challenges such as the unavailability of real-time biomechanical analysis and the need for complete automated data systems persist. Complexities associated with constructing accurate and flexible digital twin models, particularly regarding soft tissues, remain a limitation. Additionally, ensuring uninterrupted online data collection while safeguarding patient privacy poses ongoing challenges.

Despite these limitations, the integration of Industry 4.0 and digital twin technology holds immense promise for the future of healthcare. As advancements continue, the potential for precision medicine and personalized healthcare interventions becomes increasingly attainable. By addressing current challenges and leveraging emerging technologies, stakeholders across the healthcare spectrum can position themselves at the forefront of this paradigm shift, ushering in a new era of intelligent and patient-centric healthcare solutions.

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