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RESEARCH ARTICLE

Elaboration of Innovative Digital Twin Models for Healthcare Monitoring With 6G Functionalities

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ABSTRACT Remote monitoring of individuals with special healthcare needs and controlling their living spaces using emerging technologies is a significant focus for researchers from various disciplines, forming a crucial element of future healthcare development. Digitizing the healthcare sector demands expertise and knowledge transfer to create new paradigms and innovative solutions to enhance life quality and reduce healthcare burdens. One of the most promising technologies in this area is the Digital Twin (DT), a virtual replica of the real world with advanced features for data clustering, classification, and forecasting. This paper introduces an innovative context-aware framework for monitoring indoor air quality and human activity, integrating technologies like the Internet of Things (IoT), 6G networks, sensing and localization techniques, Edge Computing, Deep Learning models, and cloud platforms. The multidisciplinary research emphasizes the interaction of the DT concept with its environment and other technologies. The contributions include: establishing an architecture with sensors, gateways, and a DT object on Azure cloud, validated with AI models; linking 6G network sensing and communication capabilities with IoT-based techniques to enhance performance; and developing deep learning models for Human Activity Recognition (HAR) using inertial sensors, achieving a test accuracy of 99.34% and a real-time accuracy of 92.10%.

INDEX TERMS IMU sensors, deep learning, edge computing, 6G, terahertz frequency, IoT, azure cloud, DT.

I. INTRODUCTION

Over the past ten years, there has been significant growth in the provision of networking services aimed at a variety of applications with specific requirements, covering areas ranging from agriculture to education to tourism and health services. Although many services have been automated through the use of intelligent applications, human intervention remains essential, especially for data collection. This activity has become tedious for individuals because these systems require a large amount of data to refine their results. Thus, the idea of automating data collection was proposed. To this end, new architectures allowing instantaneous data collection have been suggested. Nowadays, the best solution for a precise and immediate analysis of human needs is the notion of digital twins. This innovative process relies on automation, requiring process orchestration and synchronization. For this, a holistic system composed of orchestrated components, paradigms and decisions was proposed.Traditionally, the healthcare field was considered a distinct discipline, where doctors, nurses, caregivers and pharmacists constituted the main human resources. However, with the advent of new technologies such as the Internet of Things, cloud computing, artificial intelligence, cybersecurity and ultra-high performance communication systems, new disciplines and specific level of expertise have been introduced into the health sector. These advances aim to create a complex system that coordinates multiple tasks, achieves various goals, improves decision-making, and optimizes the use of shared resources. DT, as a complex system that extends IoT concepts, new communication techniques, theory-based modeling and processes, and decision-making approaches, is one of the new potential technologies offering a wide spectrum of new services and a plethora

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of operations to digitize, scale, automate, optimize, and improve the quality of life and optimize resources. The DT is a digital replica of the physical world, integrating sophisticated components such as cloud storage, functions for task automation, artificial intelligence models, and decision-making capabilities. The idea of a DT first appeared in the product lifecycle management course taught by Michael Grieves around 2002 [1]. The number of research articles rose considerably starting from 2010 when John Vicker introduced the term DT from NASA, it was related to space and earth studies and imaging, reflecting the need to build a virtual replica of the real world with additional functionalities and intelligence.The DT idea is older and was related to all tasks, models, and activities preceding and following the manufacturing of a given product to optimize the operational and maintenance cost. The DT idea exists in the past in some monitoring platforms, such as Operation & Maintenance Center(OMC) architecture, for wireless cellular networks to monitor an extensive wireless distributed network and alarms and possible failures. In this context, DTs existed in the past without consideration of new components such as artificial intelligence(AI), cloud services, the Internet of Things (IoT) paradigm, and network flexibility and agility. The main drivers of the new vision of the DT are the new emerging technologies in networking, sensing, and communication. DT concept requires open access to the cloud, edge network, and IoT network, interfacing with existing networks, and ease of use capability. DT can revolutionize the healthcare sector by introducing new services and optimizing resources to assist vulnerable persons with small human interventions when needed. DT can improve the quality of life using AI models to forecast and classify activities and detect abnormalities in the living environment. Vulnerable people, including aged persons and people with long-term diseases, are prone to incidents, and their physical activities are limited and need continuous monitoring. Staying inactive for a long time in indoor places can trigger serious health consequences, including the development of diseases such as diabetes, blood lipid problems, heart disease, and colon disease [3]. According to a recent United Nations Department of Economic and Social Affairs report, the number of people aged sixty and over is expected to grow to 2.1 billion by 2050. This will increase the burden on the healthcare system to provide an acceptable quality of life and care. This statistic highlights the impending pressure on healthcare resources, as nearly 50% of healthcare resources are dedicated to caring for the elderly [3]. Traditionally, long-term care facilities (LTCF) or nursing homes have been the solution for elderly people. Living in these facilities can often lead to older adults losing their independence and experiencing depression. To enable older adults to complete their daily lives independently, it is crucial to transform residents into smart environments. This transition can be seen as a sustainable solution that provides a sense of independence, prevents social isolation, and promotes family self-sufficiency. Sensor technology advancements without affecting residents' privacy (e.g., strategically placed motion, door, and temperature sensors in homes) [4]. The power of deep learning models in identifying daily activities [5] and the use of information and communication technologies (ICT) [6] facilitate communication between families and caregivers and pave the way for assisted living. The concept of assisted living effectively aids older adults in maintaining a degree of independence in daily activities at home [7]. There are still gaps that exist in connecting caregivers with elderly homes. To bridge these gaps, a fundamental shift toward digital transformation becomes necessary, where creating a virtual counterpart allows caregivers to control and interact in real-time within the digital space. Incorporating a DT facilitates this digital interaction by establishing a conduit through a knowledge graph [8]. We developed a DT framework leveraging state-of-the-art technology to address the challenges mentioned earlier. In this framework, deep learning models embedded in edge devices handle the classification of human activities and seamlessly synchronize the data of environmental parameters. The combined data is transferred to a cloud-based DT, where a knowledge graph visually represents the information. Our contributions in this paper can be summarized as follows:

1) Experimental setup including data collection using Raspberry PI and sensors, the configuration of non-standalone DT using Microsoft Azure platform supporting cloud services and sophisticated functionalities, and finally establishing the link between the DT and sensors via the edge hardware.
2) Elaboration and integration of time series AI models for human activity recognition(HAR) at the edge using data collected from IMU sensors, the choice of using the edge to host HAR models is constrained by hardware capabilities and other QoS requirements.
3) Proposing a theoretical framework for 6G join sensing and communication based on beam forming and steering assisted by a DT, including assessment of localization error and sensing.

The paper is structured as follows: Section II explores related research works. Section III presents our proposed framework. Technical details about the experimental setup are provided in Section IV. Next, Section V presents the experimental results. Finally, Section VI concludes our findings.

II. RELATED WORKS

In recent years, the DT has indicated great potential in the areas of smart homes and smart healthcare. This part provides an overview of related works, as briefly summarized in table 1, and provides detailed information in the following subsections.

A. DT FOR SMART HOME

DT has been considered a promising solution to smart home problems such as resource management and security management. It is reported [9] that real-time management of

TABLE 1. DT applications for smart home and healthcare.

Field	Literature	Main Contributions	Technologies
Smart Home	DT Energy [9]	Developing a DT and cloud platform for real-time building management.	BIM, DT, XR
	DT lighting [10]	Visual management and intelligent lighting control systems are powered by DT-driven methods based on computer vision	DT, Computer vision
	DT DT air quality management [11]	Model-Driven DT Engineering on indoor air quality management using Edge and Cloud computing	DT, EC, CP, ML
	DT for modern house [35]	Developing a realistic 3D model of DT of modern house suitable for visualization and engineering simulation	DT,AI,sensing,3D model,VR
Healthcare Monitoring	Cloud DTH architectural [12]	Architectural framework and key requirements of HDT,technical challenges and future directions	DT, ML, CP, EC
	Cloud DTH [13]	Reference framework of Cloud DTH and construction of DTH model for elderly monitoring	CP, DT
	Intelligent DT [8]	A framework that replicates the elderly home using DT in a digital space and monitor daily life activities using deep meta-class sequence models.	DT, CP, DL
	DT-assisted Blockchain [14]	Context-aware physical activity monitoring using DT and Blockchain	DT, IoT, DT, FoT, CoT, Blockchain
	Cloud DT [15]	DT model aimed at improving health monitoring in smart homes, with intelligent algorithms for fall detection and atrial fibrillation prediction	DT, DL, CP, 3D model
	Edge Cloud RPM [16]	Remote patient monitoring system based on federated LSTM for privacy-preserving smart healthcare	DT, ECC, DT
	SmartFit [17]	DT system that helps trainers to optimize actions of athetes 'behavior by computing trustable predictions of the real or spoofed users .	DT, ML
	Human Motion DT (HMDT) [37]	InMoDT which aims to capture and estimate human motion accurately	DT
	Respiration DT (ResDT) [36]	ReDT aims to monitor and classify patient breathing patterns, including both binary and multi-class classifications	DT,PCA,ML

building energy can be achieved using a DT platform based on Building Information Modeling (BIM) and Extended reality (XR). In [10], a computer vision-based DT driving method is proposed to intelligently control lighting systems and improve the energy efficiency of smart buildings. Govindasamy et al. [11] worked on model-driven DT engineering which focused on air quality management. This example applies the former to monitor carbon dioxide, temperature, and humidity levels in rooms within a building. These values could be used to develop measures to increase work efficiency and reduce the risk of viral infection. Furthermore, in [35] the authors used artificial intelligence, advanced sensors and virtual reality (VR) to develop a sophisticated DT of a modern house. The process involved creating a realistic 3D model of the house, suitable for both visualisation and engineering simulation, and establishing it as a standalone DT. The DT was updated in real-time by various sensors installed in the physical house to reflect any changes.

B. DT FOR HEALTHCARE MONITORING

The DT, a complex system of processes and components, has been considered an attractive tool for monitoring physiological parameters, proactive early disease detection and managing fitness, advanced and precise personalized healthcare services will be also delivered to reduce healthcare cost burden in broadcasting and providing the information for patients and persons with vulnerability. We present in this paragraph previous recent works on the application of DT in healthcare, emphasising the importance of digitizing and describe the overall state of the art.

In the context of personalized healthcare, Okegbile et al. [12] introduced human DTs (DTs) emphasizing the importance of addressing architectural considerations in modeling the human DTs. The authors explored the integration of emerging technologies like integrated cloud-edge computing and machine learning to empower human DTs. Finally, They provided the future research directions. Liu et al. [13] proposed a cloud-based DT framework for elderly monitoring, the DT was combined with cloud healthcare to provide high-quality services for patients, and effective management of medical data records.In addition, [13] included a case study to assess the real-time monitoring DT system's feasibility for elderly patients and discuss future healthcare challenges. In [8] Fahim et al. presented an intelligent system by combining

Cloud computing and deep learning techniques to replicate the elderly home in digital space which can offer a suitable way to monitor the resident's daily life activities aiming to deliver the necessary assistance and services. A useful approach [14] involves the integration of various advanced technologies, including the Internet of Things (IoT), DT, Fog of Things (FoT), Cloud of Things (CoT), and Blockchain. The researchers introduced an intelligent contextual physical activity monitoring framework designed to enhance sensitivity within the healthcare domain. This framework leverages deep learning models for sequential data processing to analyze the movements of elderly individuals,and detects irregular body events. Moreover, the proposed framework prioritizes the security of personal data by incorporating progressive security features provided by blockchain technology. Zhou et al. [37] developed an Inertial Motion Capture System for Human Motion Digital Twin (InMoDT) which aims to capture and estimate human motion accurately. It consists of a hub node and inertial measurement units (IMUs) attached to the body to enable accurate motion data collection. The system employs sensor fusion and pose calibration algorithms to ensure accurate orientation measurements. A DT model that is designed for health monitoring in smart homes was introduced by [15]. Two intelligent algorithms were developed to detect falls using WiFi signals and atrial fibrillation using electrocardiograms captured by wearable devices. Gupta et al. [16] presented a remote monitoring system using DT and edge cloudlet computing (ECC). which employs an LSTM-based AD model.The edge cloudlets was employed for avoiding user's data sharing and hierarchical federated learning architecture for certain computational requirements. In a similar work, Barricelli et al. [17] introduced a DT framework aims at predicting, suggesting, and then optimizing the behavior of athletes, using SmartFit which contains sensors for continuous data collection. Moreover, in [36] the researchers developed an innovative Respiration Digital Twin (ResDT) model using Wi-Fi Carrier State Information (CSI), advanced signal processing techniques and machine learning (ML) algorithms. This framework aims to monitor and classify patient breathing patterns, including both binary and multi-class classifications.

III. THE PROPOSED FRAMEWORK

In our proposal, we combined the use of Edge and Cloud technologies to create a powerful health monitoring system for real-time virtual representation of the physical environment. This enables continuous and detailed monitoring of environmental conditions such as temperature, humidity, air quality, and performed activities. Through real-time simulation and modeling, scenarios can be anticipated and system performance optimized, while advanced analysis algorithms enable rapid detection of anomalies and unusual behavior. A locally, AI model has been embedded in the Edge device to intelligently process the sensory data stream and provide information about activities performed at home. On the other hand, cloud technology serves as the Digital Twin, providing monitoring, data management, long-term storage and accessibility. In the figure 1, we present the architecture of the proposed framework.

A. PHYSICAL SPACE

The physical entity layer is the hardware foundation of the DT model framework. The physical entity layer transmits the perceived and acquired body state and environmental data to the digital layer, promoting the creation of the proposed DT model. We consider the home as a focus for elderly people to provide assistance services based on ambient sensors (i.e., motion, temperature, and humidity). These sensors detect and cover the data, then they are intelligently processed using an Edge Computing AI model to identify the individual's daily activities, synchronize them with the environmental data, and then transmit them to the DT in the cloud using the communication protocol. The AI model is the core of our proposed framework to process the sensory data and provide information about the activities performed by the person. The traditional approach of sending the raw data to the Cloud for computing, processing, and storage poses various challenges. These issues include low throughput, high latency, bandwidth bottlenecks, data privacy, centralized vulnerabilities, and additional costs (such as transmission, energy, storage, and calculation costs) [18]. To address the limitations associated with cloud computing mentioned above, the concept of edge computing has emerged as a promising solution. The use of Edge computing AI can help to reduce data transmission time and device response times, reduce the pressure on network bandwidth, reduce the cost of data transmission, and also achieve decentralization [16], [18]. In our proposed method, we utilized edge computing to implement real-time activity recognition using the Deep Learning model. The classified activity data and temperature and humidity readings are then transmitted to the virtual space. This integration enables comprehensive monitoring of environmental parameters and motion tracking. Processing data in the cloud has many drawbacks including:

- Increased energy consumption
- High latency
- subject to QoS and QoE fluctuation
- Data can be altered and additional efforts required for privacy

Moving pre-processing and data analysis to the Edge can improve latency and QoS/QoE and reduce possible attacks on data.

B. COMMUNICATION LAYER

The communication layer was designed to exchange information between telecommunication devices; the communication medium can also be shared with the DTs in parallel with existing communication systems. Therefore, DT can benefit opportunistically from RT and NRT device data, for example, medical data collected from the Wireless Body Area Network(WBAN) network. different technologies are

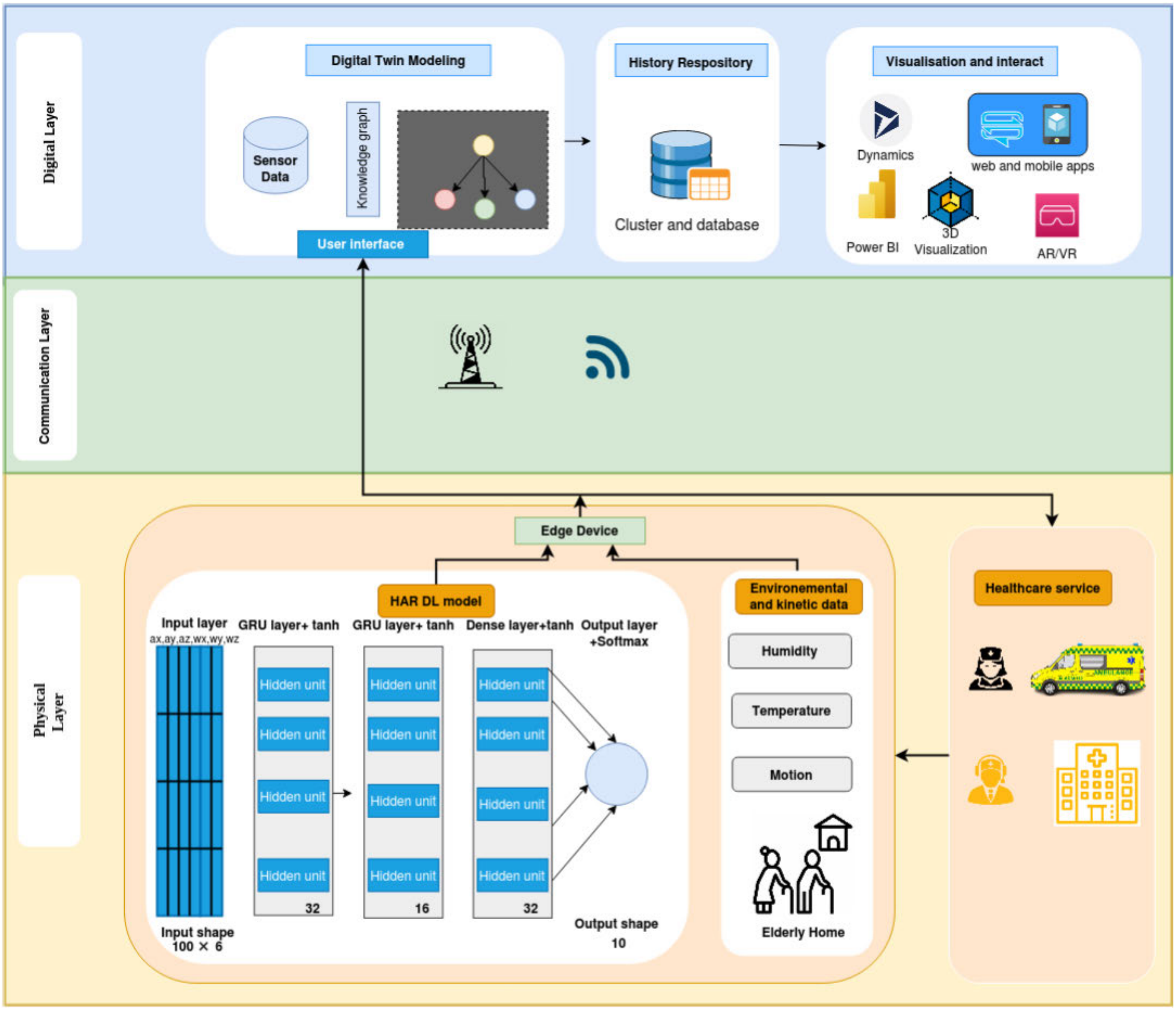

FIGURE 1. The architecture of the proposed DT framework for health monitoring consists of three layers:(a) The physical layer integrates sensors and edge devices for developing AI models for Human Activity Recognition (HAR).(b) The communication layer facilitates data transmission. (c) The digital layer includes the DT, historical reporting, and visualization tools.

available for data transmission with different requirements, architectures, and communication mediums. A DT requires a different traffic profile with stringent and tolerant quality of services and user profiles. Most DT studies focus on the tolerant quality of services(QoS) approaches to exchange low data rate traffic with low delay; however, for healthcare applications, one may think about ultra-high data rate with zero latency transmission to reduce response time during a local or global healthcare crisis, where a low delay is required to manage resource and make convenient rescues, moreover data rate are required if low data rate sensing channel shows some anomalies and a raw massive data should be exchanged. The new 6G technology is enabled by a terahertz band suitable for sensing small particles in the air and also achieving an ultra-high data rate simultaneously; a recent work communication and sensing models for DTs was recently proposed in [20], a research study was proposed in [21] describing how 6G features, coupled with IoT and cloud, can advance DT technology in term of accurate sensing, AI and ultra-high communication and low latency.

In this section, first, we set up our requirements for the communication layer to the following points:

- DT performs position collection and sensing tasks and assists in monitoring communication links.
- The communication layer, assisted by DT, supports Joint communication and sensing; communication should be directional to reduce interferences and multipath and support ultra-high data rate using wide bandwidth; sensing can be boosted by additional techniques to detect gases and particles in the air and measures

temperature, we limit this study to temperature and humidity measures.

- High availability: DT should be ready all the time to receive and process data from sensors and to broadcast and transmit valuable data
- The Communication channel supports mobility in an indoor environment. The DT should be able to track the position of the device to manage the beam's direction
- Physical integrity: protection of sensitive data from intrusion and modification
- High data rate: a DT can transmit and receive a high volume of data ranging from multivariate time series data to videos or virtual reality information.

To our knowledge, no existing work aligned with the proposed DTs communication channel and 6G technology requirements, where the performances of DT complement and assist the future 6G network. The second task in this section, which represents a novelty, is to assess, via modeling and simulation, some 6G techniques, such as indoor user tracking and DT-assisted beam steering using collected data, to exchange reliable ultra-high data rate multimodal data. This part will not be included in the experimental setup. DT benefits from advances in new communication technologies such as 5G, 5G advanced, and the future 6G system; 5G and beyond can deliver ultra-high data rates with ultra-low delays and good reliability in terms of packet loss rates. Among the techniques used to enable the 5G and 6G technology is user tracking and signal beam-forming using antenna arrays. The terahertz band(THz), ranging from $100GHz$ to $10THz$, offers an unprecedented wide bandwidth reaching $70GHz$ at $300GHz$ frequency and will be used in the next generation of 6G networks. Current work on the design of THz antenna demonstrates the feasibility of reaching a high data rate and improving communication range using beamforming.

A 6G access point(AP) is placed vertically at an indoor wall to transmit and receive THz signal, The AP gain is given by [24]:

$$\psi(\theta,\phi)=g\frac{\sin\left(M_a\frac{\pi f\xi}{c}\left[\sin(\theta)\cos(\phi)-\sin(\theta_0)\cos(\phi_0)\right]\right)}{\sin\left(\frac{\pi f\xi}{c}\left[\sin(\theta)\cos(\phi)-\sin(\theta_0)\cos(\phi_0)\right]\right)}\frac{\sin\left(N_a\frac{\pi f\xi}{c}\left[\sin(\theta)\sin(\phi)-\sin(\theta_0)\sin(\phi_0)\right]\right)}{\sin\left(\frac{\pi f\xi}{c}\left[\sin(\theta)\sin(\phi)-\sin(\theta_0)\sin(\phi_0)\right]\right)}$$

ξ is the inter-element spacing, f the operating frequency in Hz, $M_a \times N_a$ is the antenna array size, g is the isotropic gain, (r, θ, ψ) the polar coordinate of the mobile device against a frame linked to the antenna array as shown in figure 2. θ_0 and ϕ_0 are, respectively, the tilt angle against z-axis and ϕ_0 the azimuth angle against x-axis in the wall plane(antenna array plane). The antenna gain is maximum at the direction (θ_0, ϕ_0). Assuming that the mobile device is equipped with a THz antenna and IMU sensor to collect accelerometer and gyroscope data, the relative position can be updated as per [23]. Let $(\Delta x, \Delta y, \Delta z)$ the infinitesimal cartesian displacement of the mobile between two instants, the polar displacement $(\Delta r, \Delta\theta, \Delta\phi)$ is expressed as:

$$(\Delta r, \Delta\theta, \Delta\phi)^t = (J(r,\theta,\phi))^{-1}(\Delta x, \Delta y, \Delta z)^t \quad (1)$$

$J(r, theta, phi)$ is the Jacobian matrix. The equation of the gain and equation 1 will be implemented in the DT to perform the new beam's direction (θ_1, ϕ_1) and new distance update r_1 between the phased array antenna and the mobile device. The following equation gives the new direction and distance:

$$(r_1,\theta_1,\phi_1)^t = (r_0,\theta_0,\phi_0)^t + (J(r_0,\theta_0,\phi_0))^{-1}(\Delta x, \Delta y, \Delta z)^t \quad (2)$$

The exactitude of the beam direction depends on the estimation of the new position of the mobile using available IMU sensors on the mobile device; this operation will be performed at the DT level. Moreover, the new beam direction also depends on the previous position's Jacobian matrix. We assume that positioning error is a Gaussian random variable with mean vector $(\bar{\Delta x}, \bar{\Delta y}, \bar{\Delta z})^t$ and covariance matrix Σ_c; the displacement is given by:

$$(\Delta x, \Delta y, \Delta z)^t = (\bar{\Delta x}, \bar{\Delta y}, \bar{\Delta z})^t + \Sigma_c^{\frac{1}{2}}\mathcal{N}(0, I_{3\times3}) \quad (3)$$

Therefore, the precision of beam's direction and distance is given by the covariance matrix:

$$\Sigma_p = (J(r,\theta,\phi))^{-1}\Sigma_c(U(r,\theta,\phi))^{-1} \quad (4)$$

where, $U(r,\theta,\phi) = (J(r,\theta,\phi))^t$, the error intensity of the beams pointing error and distance can be expressed in terms of $\det(\Sigma_p)$, this intensity is given by:

$$\det(\Sigma_p) = \frac{\det(\Sigma_c)}{(\det(J(r,\theta,\phi)))^2} \quad (5)$$

The determinant of the Jacobian in our case is:

$$\det(J(r,\theta,\phi)) = r^2\sin(\theta) \quad (6)$$

Finally, the intensity of beams and distance error is:

$$\det(\Sigma_p) = \frac{\det(\Sigma_c)}{r^4(\sin(\theta))^2} \quad (7)$$

We assume that the antenna is placed in one of the walls or fixed at the ceiling of an indoor environment. In that case, the accuracy of the beam steering toward the mobile user depends on its instantaneous position. As explained before, the polar coordinate suits well for wave propagation and beam steering. The user's device position is determined using data from the IMU sensor; DT collects data from IMU to estimate position and recognize human activities. Estimated positions are mapped with polar position, and device spatial displacement is transformed into polar change to assist the THz AP in pointing its beam toward the new device's location.

Based on the result described by equation 7, to reduce the intensity of pointing error, we need to improve the performance of positioning algorithms using IMU sensors, increase the distance between antenna and mobile, the antenna height should be maximized to increase $\sin(\theta)$, However, increasing r leads to lower received power, therefore low data rate. A DT is supposed to assist in solving this issue by improving beam steering accuracy with less impact on data rate; 6G system will also possess its independent features for beam management and tracking. Therefore, 6G and DT can collaboratively enhance beam steering performance in future implementation.

Figure 2 represents the general communication architecture, including two main interfaces; the first is for low-rate communication, and the second uses a higher-rate communication system such as 5G/6G. 6G technologies outperform the existing 5G technology in terms of QoS and new functionalities; sensing the air and indoor environment is also crucial using the THz band, and the Beer-Lambert law is used to describe attenuation due to gas absorption. Moreover, the 6G communication link will carry ultra-high and zero latency signal for downlink and uplink and contribute to the channel sensing and assessment of air quality. The absorption loss due to atmospheric factors is given by:

$$L_{atm} = e^{-[a_d(f,T,P)+a_h(f,AH,T,P)]r} \tag{8}$$

where f is the frequency in GHz, T temperature in $^\circ C$, P is the atmospheric pressure in Pascal, r the path propagation length in meters and AH is the absolute humidity expressed in g/m^3, a_d attenuation for the dry environment and a_h attenuation with humidity. Based on ITU-R P.676-10 recommendation [22], electromagnetic molecular attenuation exists for frequencies higher than $10GHz$, mainly water vapor, and oxygen. We assume in 8 that the indoor environment is a mixture of different gases, such as water vapor(H_2O) and oxygen(O_2); other gases can exist and interact with 6G signal but will be studied in future works. DHT11 measures temperature and humidity data in the room, the values stored in the DT repository. the gas mixture, water vapor, and others, along with temperature and pressure, will affect the received signal; the DT will inform the 6G AP about the required transmitted power to overcome this molecular loss. Moreover, the THz link can assess the loss in particular frequency windows; however, this operation is complex and requires additional THz sensors. This paragraph aims to highlight the relationship between the 6G signal and data measured by sensors; sensor data can improve the 6G power management by recommending the convenient transmitted power if the molecular loss is high, and also performing extensive sensing of the air using the mmwave/THz frequency band. Figure 8 presents the power loss of the received signal as a function of atmospheric parameters, distance, and gas concentration. We used the ITU model [22].

C. DIGITAL LAYER

The implementation of a DT model addresses the limitations of traditional activity recognition systems [25], [28], [29], [30]. In traditional systems, sensor data are transferred to a machine-learning model for activity recognition, but there is no way to interact with the home and understand the underlying behavioral patterns [8]. However, using the DT technique the caregivers and doctors can access and monitor the home environment in real-time, ensuring privacy and providing valuable information. The DT not only provides real-time access to the user and home but also advanced storage, analysis, and management of data. If the DT detects a critical situation or abnormal behavior, it can trigger notifications or alerts to caregivers or healthcare staff. Major companies such as AWS,[1] Eclipse,[2] and Azure [3] have started to offer a platform for creating and operating DTs in cloud environments.

IV. EXPERIMENTAL SETUP

In this section, we describe the main steps for the experimental setup of our proposed framework involving available open-source technologies, hardware used, communication protocols, and tools, emphasizing data flows and interactions. The aim is to build our proof of concept(PoC) fulfilling the proposed tasks of the DT as specified in section III. In figure 4, we present the architecture of the proposed experiment highlighting all devices such, as communication protocols, the type of data collected, and the Cloud services.

A. PHYSICAL LAYER CONFIGURATION AND SETUP

In our scenario, the physical twin represents the user motion and their living space such as atmospheric variables. We utilized specific hardware for sensing to collect data and pre-processing activities. The hardware part of the experiment consists of: carte Raspberry Pi 4 with a quad-core Cortex-A72 processor and 2 GB of memory was used as an edge gateway device, an iPhone 11 Pro Max smartphone including an inertial measurement unit (IMU), this unit includes an accelerometer and gyroscope sensors, The edge device will be linked to the mobile phone to process IMU data. The Raspberry Pi is connected to a DHT11 sensor that gathers humidity and temperature data. These measurements are sent as raw data to DT. Additionally, the Raspberry Pi integrates a pre-trained Deep Learning (DL) model for Human Activity Recognition (HAR). The controller, connected to the internet via WiFi, enabled easy reading and sending of the resulting data to the Cloud DT. We developed a Python script running on the Raspberry Pi to streamline this process. This script collects data from the DH11 and IMU sensors.

To recognise human activities using AI models and collected data, the following steps will be followed:

1) DATA COLLECTION AND PREPROCESSING

The dataset was gathered from a group of 5 subjects ranging in height from 1.54 to 1.78 meters. IMU data

[1] https:/https://aws.amazon.com/fr/greengrass/
[2] https://eclipse.dev/ditto/
[3] https://azure.microsoft.com/fr/products/digital-twins/

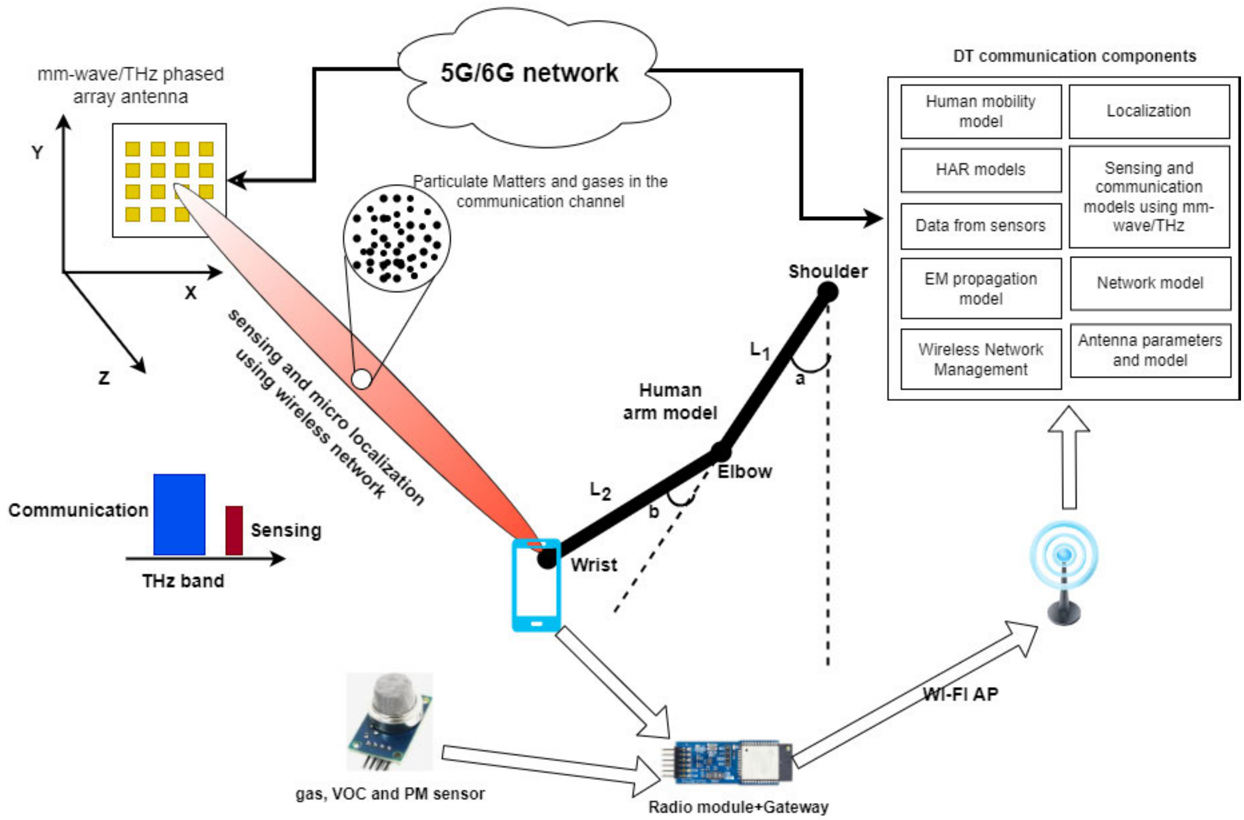

FIGURE 2. **A different vision of the DT emphasizing the communication and sensing part, collected data of mobility, air quality, and atmospheric variables will be collected using associated sensors and transmitted to the gateway, processed, and re-transmitted to the DT via WI-FI access point. The decision will be made if a user needs to downlink ultra-high data rate data using a 5G/6G network; phased arrays will then receive a command to steer their beams toward the user to perform communication and additional sensing.**

was collected by attaching smartphones to each subjects waist to measure 3-axis acceleration and velocity data. Each participant performed one of the following ten activities: falling, sitting, walking, standing, lifting, lowering, ascending stairs, descending stairs, getting up, or sitting down. The minimum number of repetitions was 5 for each activity. Each activity was performed for 6 seconds and data were recorded at a sampling frequency of 100 Hz. The data collection process was simplified using the Physics Toolbox Smartphone application, a flexible tool for recording sensor data. All collected data was then transferred to the PC, where it was stored as a CSV for preprocessing and subsequent analysis. In total, 150,000 samples were collected during this process.

After collection and cleaning the sensor data, a data augmentation technique was employed to increase the size of the dataset by adding white Gaussian noise [19] to the sensor data signal with zero mean and a std of 0.02.The augmented samples were combined with the original cleaned dataset, resulting in a final augmented dataset. A samples attributes of our dataset are presented in figure 5. The figure 6 shows the number of samples for each activity type after applying the data augmentation. Various preprocessing steps were applied to the input to enhance the dataset's quality before feeding it into the deep learning models. Initially, 5-point moving average filters were applied for all samples to smooth and remove the noise from the signal. Secondly, a global normalization was used using the maximum and minimum values of the recordings to maintain the magnitude information of each activity [23]. Also, we used a sliding window overlap technique [23] to balance the epoch datasets of the ten activities. In this work, a sliding window size of 100 with 20 overlaps was used. Finally, data segmentation was performed, and the dataset was divided into training (80%)and testing(20%).

2) DEEP LEARNING MODELS ARCHITECTURES FOR HAR

In this study, we used and trained four deep-learning models RNN, LSTM, BiLSTM, and GRU. These four models have demonstrated their merits and advantages over previous sensor-based HAR works [8], [23], [25], [32]. Figure 7 shows the architecture of these models. We used Python 3.9 with TensorFlow and Keras libraries for training and testing models. All models were trained 180 epochs each with The Adam optimizer, learning rate of 0.002, batch size of 32, and Tanh as activation function.

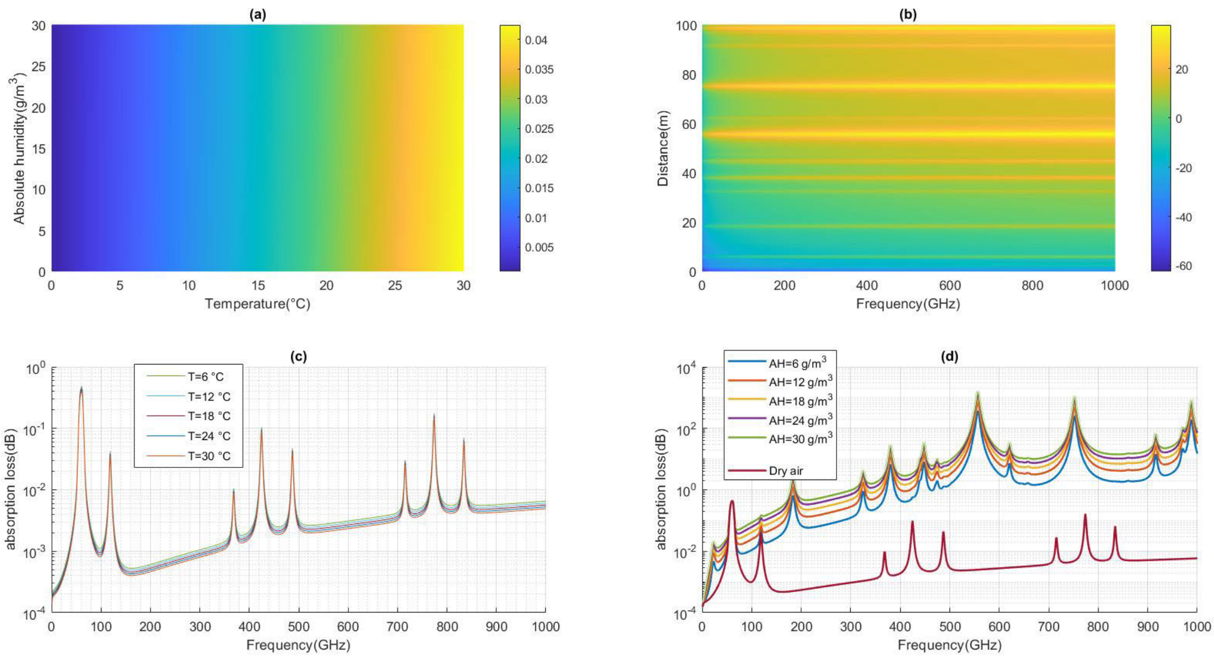

FIGURE 3. Simulation of molecular absorption, for constant atmospheric pressure $P = 101300Pa$, as a function of frequency, distance, temperature, water vapor concentration, and dry air. (a) heat map plot of the molecular attenuation as a function of temperature and water vapor concentration(b) heat map plot for the molecular attenuation as function of frequency (GHz) and distance(m) for given concentration and temperature(c) attenuation due to variation of temperature as a function of frequencies for dry air room (d) attenuation due to humidity and for dry air as a function of frequencies.

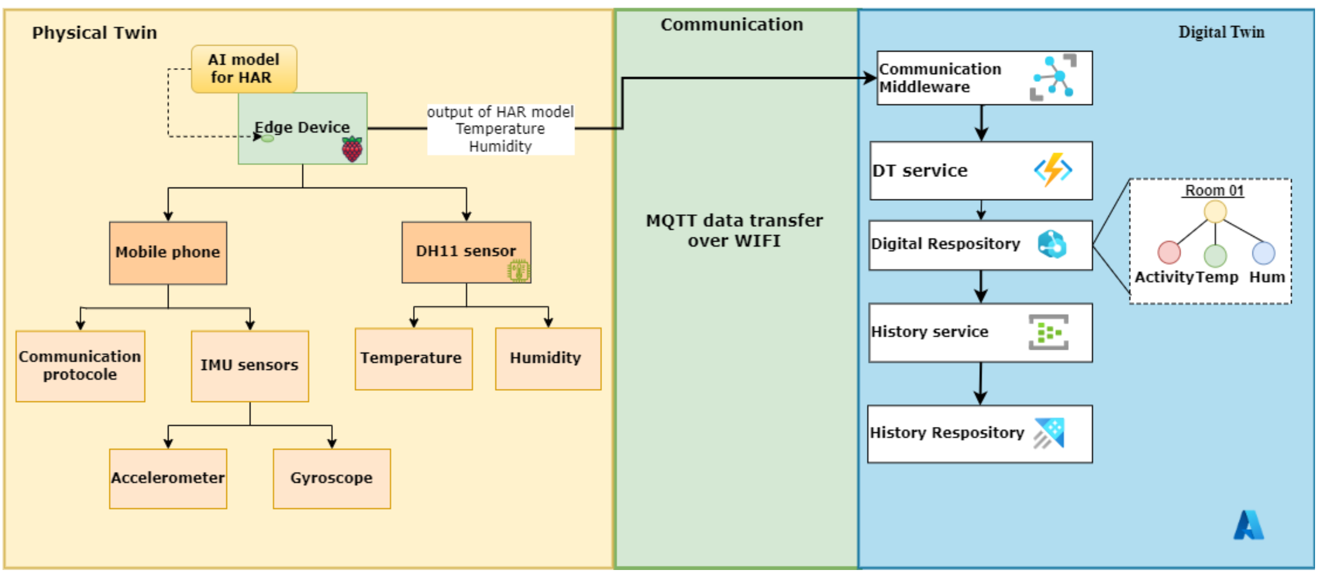

FIGURE 4. Experimental setup of DT implementation: The mobile phone device is connected to the edge device using BLE protocol and DHT11 sensor linked to the edge device via wired connection, the communication protocol used to transfer data from edge device to the DT is MQTT over WIFI connection.

- Recurrent Neural Network
  Natural language processing (NLP) or speech recognition problems use the RNN model as a basic framework to extract features and patterns from sequential activity signals. In contrast to feed-forward neural networks, the RNN model processes data recurrently and uses hidden states, which are commonly known as memory components, on each node to maintain sequential information from past input data. Our performed RNN model as shown in 7 is composed of a total of three

	Time stamp	Acc_x	Acc_y	Acc_z	Gyro_x	Gryro_y	Gryro_z	Activity	Activity num
1	2023-09-24 11:28:59.1510	0.596523	0.589062	0.422904	0.448422	0.538041	0.620168	Falling	0
2	2023-09-24 11:28:59.1340	0.591593	0.597821	0.396101	0.459977	0.538329	0.622009	Falling	0
3	2023-09-24 11:28:59.1410	0.596056	0.590093	0.409747	0.452086	0.538904	0.620986	Falling	0
.....	....	......	....	....	....	....	....	......	....
286364	2023-10-04 13:19:55.0610	0.675639	0.506101	0.535239	0.506849	0.372683	0.603015	Getting up	1
286365	2023-10-04 13:19:55.0710	0.676979	0.514303	0.522654	0.500527	0.373902	0.605528	Getting up	1

FIGURE 5. Samples attributes of our dataset after applying data augmentation technique.

RNN layers with 32 units followed by a dense layer with 32 hidden units and an Softmax layer with ten output neurons.

- Long-Short-Term Memory
  The LSTM model is an improved version of RNN. It can solve the problem of vanishing gradients by retaining feature information longer. The model uses a mechanism consisting of three gates, namely forget gate, input gate and output gate. The process begins with the forget gate deciding what relevant information to retain for the current LSTM unit based on the hidden state of the last state and the current input value. Then Input gates determine what new data can be added from the current time step. this The new context state is updated based on the results of these two goals. Finally, the output value create a new hidden sum between the initial context state and the current input Context state for the next LSTM model [25].The LSTM classifier as shown in Figure 7 consists of two unidirectional LSTM layers. Each of the LSTM layer consists of 64 units followed by two fully connected dense layers. Each one with 128 units.The last layer was a softmax with ten output neurons.
- Bidirectional Long-Short-Term Memory
  The Bidirectional Long Short-Term Memory (BiLSTM) model allows input flow in both directions (backward and forward). The BiLSTM model allows the extraction of features related to future and past time steps [27] Our BiLSTM model as presented in Figure 7. The model architecture consists of two BiLSTM layers. Each one consists of 128 units followed by a dense layer with 254 neurons and a SoftMax layer with ten neurons for classification.
- Gate Recurrent Unit Gated Recurrent Units (GRUs) is a compact neural network version of LSTM that removes contextual state. The GRU model only uses hidden states to convey previous relevant information. The model is used to maintain memory capacity in a compact form, which can reduce the number of tensor operations and train the model faster [27]. Our implemented GRU model as shown in Figure 7 consists of two GRU layers. Each GRU layer contain 32 units followed with one fully connected layer consists of 32 neurons and a SoftMax layer with ten output neurons for classification.

3) EVALUATION METHOD

To evaluate the effectiveness of the models, we employed the k-fold cross-validation (k-CV) technique, K-CV averages multiple hold-out estimates from different data splits. It randomly splits the data set into k separate folds, ensuring that each fold is of roughly the same size. One fold is used for testing, while the model is trained on the remaining $k-1$ folds. By repeating this process k times, the overall performance is calculated by averaging the accuracy obtained from each iteration [38]. Specifically, a value of $k = 5$ is chosen. We assess the classification performance of the four deep learning models by comparing accuracy, precision, recall, F1-score metrics, as presented in Equations 9, 10, 11, and 12. These metrics assessed the model's ability to classify the performed activity. On the other hand,two others metrics were used to evaluate the performance of HAR models on the edge device. The inference time $T_{inference}$ represents the time needed for the model to output a classification label. The inference time is given by Equation 13. The size of the model (KB) is another important metric, as it directly impacts the

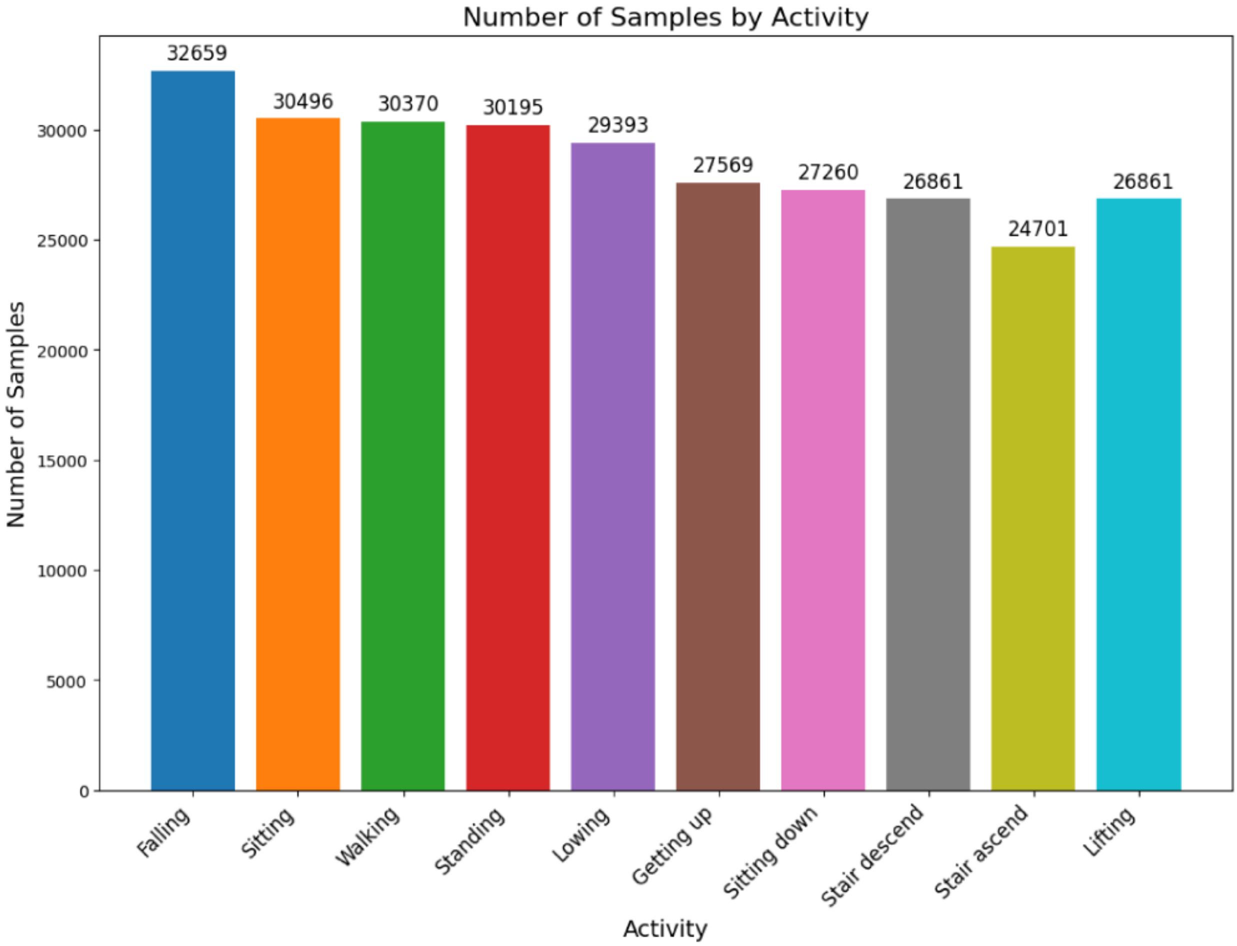

FIGURE 6. Labels distribution in our dataset after applying data augmentation technique.

memory and storage requirements of the edge device.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{10}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{11}$$

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{12}$$

$$\text{T}_{\text{inference}}(\text{ms}) = \text{T}_{\text{out}} - \text{T}_{\text{inp}} \tag{13}$$

where:

- *TP* represents the number of true positive predictions (correctly classified activities).
- *FN* represents the number of false negatives (missed classifications).
- *TP* (True Positive) represents the number of samples with correct prediction results.
- *FP* (False Positive) represents the number of samples whose result was wrong.
- T_{inp} is the time value when the data is input to the model.
- T_{out} is the time value when the resulting classification label is obtained.

B. COMMUNICATION PROTOCOLS

After testing, evaluating and comparing the performance of the various HAR models, we selected the most suitable one for the Edge. The classification result from the HAR model was then synchronised with the temperature and humidity data and transmitted to the cloud.In our case, we used the Azure platform as a service to create the DT. Azure IoT Hub [4] act as the cloud gateway. The IoT hub supports MQTT over WebSockets, AMQP, AMQP over WebSockets, and HTTPS, with bidirectional communication support. There are different typologies for direct or indirect device connectivity. The Azure IoT Hub received data as telemetry using the MQTT protocol (Message Queuing Telemetry Transport) protocol [33]. The edge device was authenticated to the Azure cloud service using a key provided by the Azure platform. Furthermore, a virtual implementation and setup is proposed for next generation 6G network, we proposed to

[4] https://azure.microsoft.com/en-gb/products/iot-hub

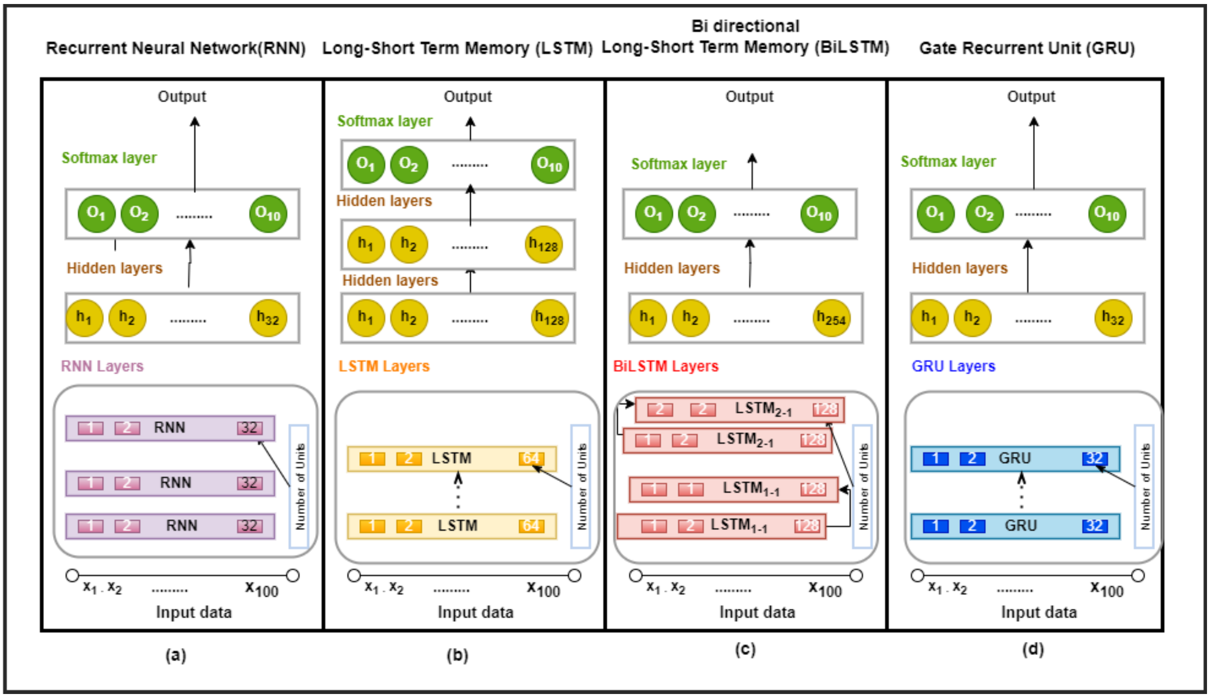

FIGURE 7. Comparison of Deep Learning model structures for sequence modeling: (a) Recurrent Neural Network (RNN), (b) Long Short-Term Memory (LSTM), (c) Bidirectional LSTM (BiLSTM), and (d) Gated Recurrent Unit (GRU).

link the DT to the 6G access point, to steer its data to the user. Works related to 6G communication is performed using MATLAB to simulate the channel attenuation in presence of user movement and atmospheric parameters such as humidity and temperature.

C. DIGITAL TWIN CREATION AND IMPLEMENTATION

Previous works on DT configurations and creation for healthcare applications can be found in [31], [11], and [16] respectively, we used Azure DT service[5] to create DT of the elderly room. It is acts as DT Repository. Azure DT is written in DT Definition Language (DTDL).[6] DTDL is used along with JavaScript Object Notation for Linked Data (JSON-LD). In this framework,the JSON-LD representation of the Elderly Room Interface, including properties for Temperature, Humidity, and Activity is shown in 8. Azure DT uses Explorer[7] for visualization, write queries, and edit models and relationships. The IoT Hub service acts as the Communication Middleware between the Azure DT and the edge, it aggregates received messages from the edge device and forwards them to the DT service using an Azure function[8] and triggered by EventGridTrigger.[9] Every update in the DT Repository, which hosts the DT service, triggers an execution of the History Service that stores historical data of the DT in the History Repository. The Azure Data Explorer[10] cluster acts as History Repository that stores the twin property updates in database. The implementation of History Service was using Azure Event Hubs[11]

V. EXPERIMENTAL RESULTS

This section discusses the experimental results from the tests conducted on both PC and edge devices. Firstly, we presented the results of evaluating the HAR models on the PC. Secondly, we transferred them validated the accuracy, size, and inference time to determine the best model for edge devices. Then, two selected models are optimized in their architectures and embedded into a Raspberry Pi device, and the performance of these models is validated with continuous data. Finally, we select the most suitable model for the Raspberry Pi and integrate the output of this model with a cloud DT.

A. HUMAN ACTIVITIES CLASSIFICATION

The performance of the four DL models trained on our dataset was evaluated with and without the cross validation protocol. Referring to table 2 and table 3,the Bi-LSTM and LSTM models have the highest accuracy, with Bi-LSTM achieving an accuracy of 99.34 %. and LSTM achieving an accuracy of 99.27% without cross validation. After applying 5-fold cross validation, Bi-LSTM maintained its lead with an average

[5]https://azure.microsoft.com/services/digital-twins
[6]https://github.com/Azure/opendigitaltwins dtdl/blob/master/DTDL/v2/dtdlv2.md
[7]https://docs.microsoft.com/en-us/azure/digital-twins/overview
[8]https://azure.microsoft.com/en-gb/products/functions
[9]https://learn.microsoft.com/en-us/azure/azure-functions/functions-bindings-event-grid-trigger
[10]https://microsoft.com/en-us/azure/data-explorer
[11]https://learn.microsoft.com/en-us/azure/event-hubs/event-hubs-about

```
{
 "@id": "dtmi:example:ElderlyRoom;1",
 "@type": "Interface",
 "displayName": "ElderlyRoom",
 "contents": [
  {
   "@type": "Property",
   "name": "Temperature",
   "schema": "double"
  },
  {
   "@type": "Property",
   "name": "Humidity",
   "schema": "double"
  },
  {
   "@type": "Property",
   "name": "Activity",
   "schema": "string"
  }
 ],
 "@context": "dtmi:dtdl:context;2"
}
```

FIGURE 8. JSON program fragment of elderly room for Azure DT.

TABLE 2. Performance metrics of HAR from the four deep learning models tested on PC.

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
RNN	93.99	94.10	93.96	94.06
LSTM	99.26	99.26	99.26	99.27
BiLSTM	99.31	99.34	99.32	99.34
GRU	98.70	98.61	98.65	98.67

accuracy of 98.23%, while LSTM achieved 97.29%. The GRU model has a relatively high accuracy of 98.67% without cross validation technique, dropping slightly to 97.12% after applying it. When compared to other models, RNN consistently performed poorly, with an accuracy of 94.06% without cross-validation and an average accuracy of 90.09% with cross-validation. According to the confusion matrix9 of the four HAR models'classification, Bi-LSTM, LSTM, and GRU are successful in classifying all ten activities. The RNN model exhibits misclassifications, particularly between the activities of "Getting up" up and "lifting". Therefore, due to its inferior performance, especially in accurately classifying activities, the RNN model may not meet the necessary criteria to advance to the next evaluation stage on the edge device.

TABLE 3. Performance metrics of HAR from the four deep learning models tested on PC and evaluated using 5-fold cross validation.

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
RNN	91.58	89.30	89.37	90.09
LSTM	97.48	97.15	97.27	97.29
BiLSTM	98.36	98.23	98.23	98.23
GRU	97.13	97.12	97.12	97.12

1) PERFORMANCE COMPARISON WITH RELATED WORKS

In our work, the BiLSTM model achieved the highest accuracy of 99.34% compared to other trained models. Table 4 compares the results of BilSTM model and similar works. As each work tries to use a set of HAR dataset, different classifier.Those reasons make it difficult to give a precise area of comparison between the model and existing ones.

B. RESULTS ON THE EDGE DEVICE

Three of the four trained HAR models (LSTM, BiLSTM, GRU) were transferred to the Raspberry Pi for performance assessment.

The evaluation of performance of the models on Raspberry Pi included several metrics such as size (KB), interference time (ms), and accuracy. We used one subject of the collected dataset to assess the performance of these models. The results are presented in Table 5. On the one hand, the BiLSTM model achieved the best results in terms of accuracy. It reached 97.20%. However, on the other hand, it was the worst in terms of the interference time, which was higher than 102 (ms) and the model size of 7105 (kB). The BiLSTM model was dropped from the continuous HAR test with the edge device. Therefore, we selected the LSTM and GRU models because they offer a reasonable compromise between accuracy, size, and interference time.

The selected models have been optimized in their architectures by reducing the number of units in the layers. Specifically, for the LSTM model, the number of units in each layer was decreased from 64 units to 32 units, resulting a new model named LSTM-2L. In the case of the GRU model, the number of units in the second layer was reduced from 32 units to 16 units and named GRU-2L. This optimization was carried out to reduce their size and optimize interference time. After training the two optimized model with our collected dataset on PC they achieving an accuracy of 97.02%. and 95.60 % respectively. The sizes, accuracy's, and inference times of the optimized HAR models with the Raspberry Pi board and one subject as continuous data are shown in figure 10. Based on the results, we selected the GRU-2L model as the HAR model to be embedded in the Raspberry Pi. Its output (activities performed) will be transferred to the DT. This decision was made because the GRU-2L model showed

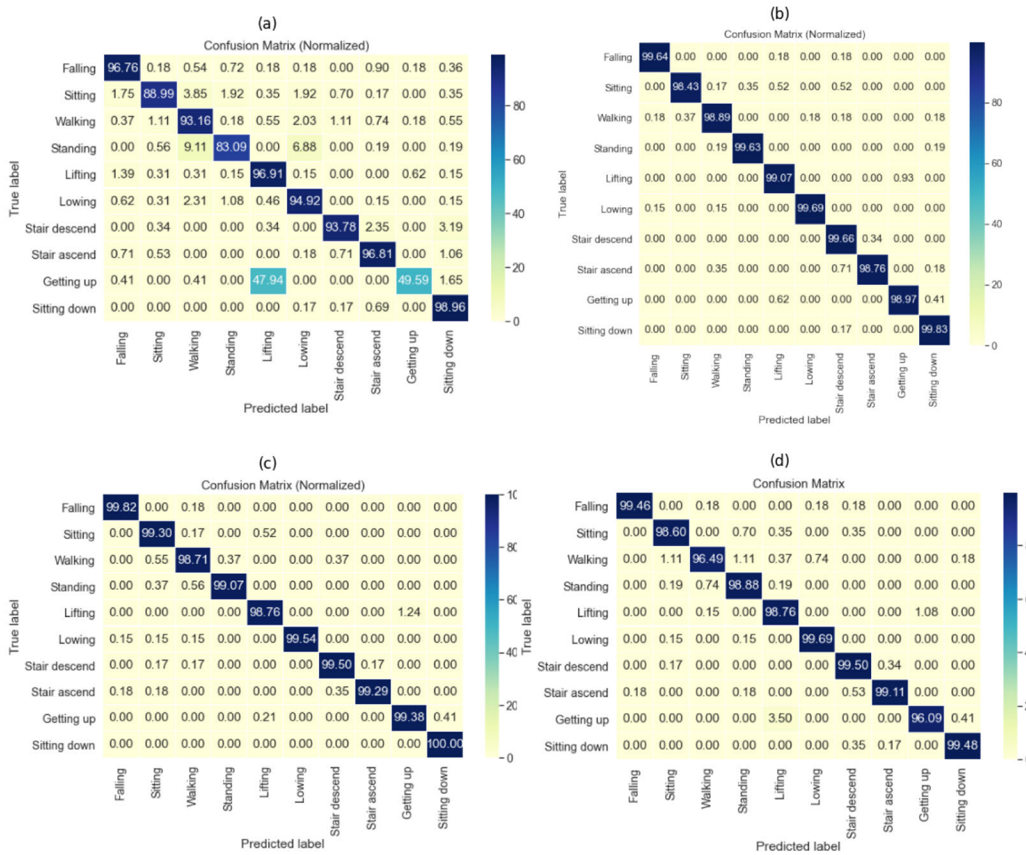

FIGURE 9. Normalized confusion matrix of each Model: (a) RNN, (b) LSTM, (c) BiLSTM, and (d) GRU.

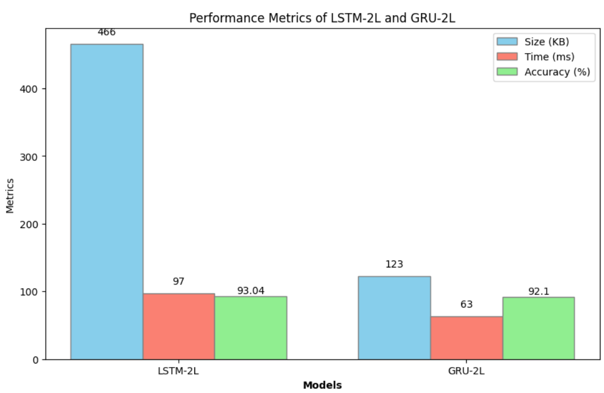

FIGURE 10. The optimized HAR models size, accuracies, and inference time with the raspberry Pi board and continuous subject.

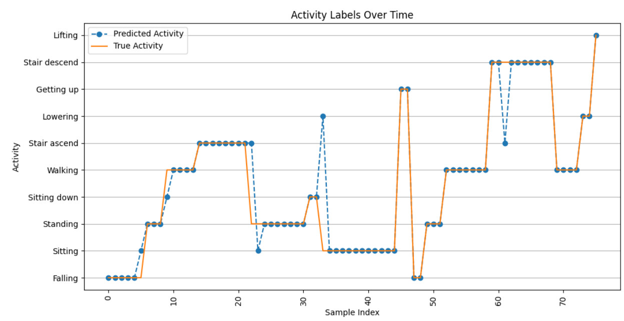

FIGURE 11. Continuous real-time GRU-2L model results from one subject in raspberry Pi.

a promising performance in terms of the size of 123 KB and the inference time of 63 ms, with only a small difference in the accuracy of 92.10% compared to the LSTM model of 93.04%.

Figure 11 illustrates the continuous HAR results against the ground truth activity labels using the GRU-2L model, and the figure presents the correspondent confusion matrix in figure 12. The HAR results demonstrate accurate classification overall. Occasionally, there are instances of confusion during transitions between activities, which indicate occasional errors in classification when one activity transitions to another. The classes of selected HAR model was synchronized with DH11 reading data of temperature and humidity and transferred as telemetry to IoT hub.

C. IOT HUB STATUS

The IoT hub, the interface component of the DT at the cloud side, receives MQTT messages for the edge.

TABLE 4. HAR model performance comparison with related works.

Reference	Locations	Sensors	Activities	Classifier	Accuracy (%)
Ramya et al. [26]	Waist	Accelerometer	Lying, Sitting, Walking, Standing, Downstairs, Upstairs	2D CNN-LSTM	91%
Boujnah et al. [23]	Waist	Accelerometer, Gyroscope	Walking, Sitting, Standing, Falling	LSTM	97.15%
Nia et al. [34]	Wrist, Ankle, Waist	Accelerometer, Gyroscope	Walking, Sit up, Jogging, Upstairs, Downstairs, Walking on the heel, Walking on the toe, Standing	RFC	97.67%
Mekruksavanich [30]	Ankle, Knee	Accelerometer, Gyroscope	Walking, Jump, Lie down, Sit, Stairs down, Stairs up, Stand, Walk	ResNeXt	97.68%
Our proposed method	Waist	Accelerometer, Gyroscope	Walking, Sitting, Standing, Falling, Stairs down, Stairs up, Lifting, Lowering, Sitting down, Getting up	BiLSTM	99.34%

TABLE 5. HAR accuracies, model sizes, and inference time obtained from one subject with the Raspberry Pi and our dataset.

Model	TIME (ms)	SIZE (KB)	Accuracy (%)
LSTM	102.10	957.20	94.23
BiLSTM	264.27	7105.73	97.20
GRU	83.55	183.09	93.60

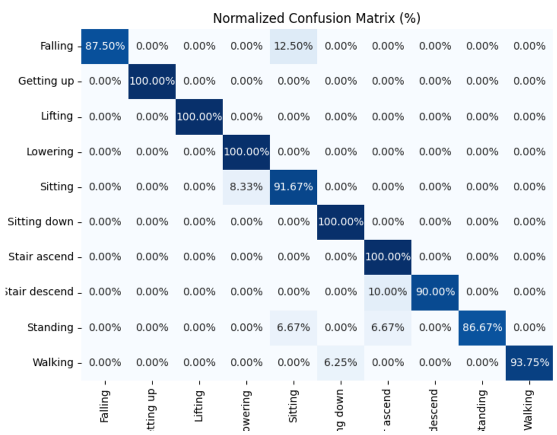

FIGURE 12. Confusion matrix of continuous real-time GRU-2L results from one subject in raspberry Pi.

Messages contain raw data and HAR classes As described in subsection IV-B, temperature and humidity are exploited to determine the molecular attenuation loss of the 6G signal. This data will be used to build an outlier detection AI model to detect extremely abnormal values. IMU data are also used to predict the pointing error of the beam directed to the user, the user in some circumstances; it requires a high data rate and available service to contact the hospital or his doctor.

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed a multi-layered DT architecture encompassing physical, communication, and virtual layers to empower the healthcare sector applications. The proposed architecture collects kinetic data using IMU sensors and indoor environmental data using DHT11 sensor for temperature and humidity measurement. The Collected data from IMU are used to train deep learning models for human activity recognition. The model achieved a test accuracy of 99.34%. The model was deployed at the edge to aggregate sensor data and transmit it to the IoT hub via MQTT messages. Moreover, through theoretical and simulation studies, we demonstrated how raw sensor data can be utilized for managing indoor 6G networks, addressing key parameters like phased array beam steering pointing error and attenuation loss due to molecular attenuation. However, our work has identified some limitations. We observed a decrease in accuracy after transferring the trained DL models to the edge, indicating a need for improvement in edge computing capabilities. Additionally, misclassifications were noted between similar activities, such as stairs ascend and descend or sitting down and lowering. To address these limitations, we plan to explore advanced hardware options, like Nvidia GPUs, for direct model training on the edge. We also aim to refine our activity recognition models to better distinguish between similar activities. We will focus on collecting more data and deploying new sensors, and new AI models. For multivariate data, we will exploit the spatiotemporal distribution and tune theoretical models for 6G network resource management to deliver required QoS. AI models will be deployed both at the edge and the cloud, and simulators will be linked to the DT for prediction. In addition, we expect to enhance the DT with a 3D model and integrate VR technology to provide a more comprehensive and immersive healthcare solution.

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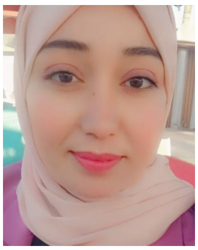

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