Implementation of Digital Twinning of Multiple Sensors on a Cloudlet System built using Qualcomm Snapdragon 410c

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***Abstract*—Industrial Internet of Things and Industry 4.0 has attracted much attention recently. A significant roadblock in Industrial IoT systems is the data privacy. The data collected from a manufacturing unit is confidential and usually large in volume, with data variations happening at high speeds. The latencies are high when the industrial system is connected to the cloud based on the bandwidth availability. Various paradigms such as Fog, Edge, Dew and Cloudlet systems have emerged over the last few years as an alternative to clouds. Edge computing would require a single powerful processing unit to handle large amounts of data, not only in terms of volume but also in terms of speed. Hence, cloudlets, which are closely related to edge computing but can be built using multiple medium-scale processing units such as System on Chips, provide an attractive alternative to clouds. In this paper, we have built a cloudlet system using multiple Snapdragon 410c and implemented a digital twining system on it. Any form of digital twining requires a powerful graphic processing unit. However, we have been able to achieve the same level of accuracy using a distributed cloudlet framework. Cloudlet system opens various avenues in the usage of IoT for industrial manufacturing systems, starting from design to predictive maintenance and also offers a scalable solution to cater to varying scales of industries, from small scale to industry complexes.**

***Index Terms*—Digital Twining, Cloudlets, IIoT, SoC and End Devices**

I. INTRODUCTION

The Industrial Internet of Things (IIoT) [1] is an essential element of Industry 4.0 [2]. IIoT uses the power of smart machines and generally does real-time data analysis to use industrial machines better. The smart machines have various sensors and actuators connected to the machines to monitor, control and analyze data in real-time. They communicate their data for further processing to a cloud or a server to enable faster and more accurate business decisions.

IIoT is used across a range of industries varying from manufacturing [3], logistics [4], oil and gas [5], transportation [6], mining [7], aviation [8], energy [9], and more. Its focus is to optimize operations, particularly the automation of processes and the maintenance of the equipment.

Implementing IIoT for any industry in manufacturing that produces physical products or manages product transportation will increase operational efficiencies, which will impact the way to create entirely new business models. It has a range of applications in a cross-section of industries, such as supply chain [10], healthcare [11], retail [12], logistics [13], production [14], building management [15], robotics [16], medical devices [17], and software-defined production processes [18].

Industry 4.0 aims to automate all traditional industrial practices, and it hopes to do so by bringing as much of the equipment from the physical space into the virtual domain. Furthermore, this is where digital twins come into play.

The term digital twin was coined in 2002 [19]. It was used to monitor and maintain remote equipment deployed in inaccessible terrains. Initially, digital twinning was done to design, model and analyze to figure out design glitches and simulate the complete system before manufacturing it.

Current digital twins are designed to build a virtual 3D model using large amounts of raw data from the actual system. Digital twins accurately simulate, analyze and even predict real-time events using real-time data from the physical world. To summarize, digital twins are virtual representations of the physical product. There can be a real-time connection between the physical world and the virtual model if data is relayed to it in real-time and the digital twin's behaviour varies with the data received from its physical counterparts.

The correct behaviour of a real-time digital twin depends on the logical results of computation and the timing constraints. Modern large-scale digital twin deployments often rely on cloud-based architectures to handle the large amount of data that needs to be stored and analyzed. Using cloud-based architecture introduces end-to-end latencies in data transmission. A significant amount of time is spent moving the data from the end devices to the cloud. Also, the issue of data privacy is paramount in Industrial systems, which prefer large local servers to remote cloud access. In this paper, we propose a solution that will bring the cloud closer to the End devices and ensure data privacy with minimum control overhead. We have used Cloudlets built using multiple Qualcomm Snapdragon 410cs [20], to build a cloudlet system which will be physically close to the End device. This system reduces the latency; simultaneously, we establish a secured communication channel between the end device and between the cloudlets using a custom network protocol stack. The rest of this paper is organized as follows: Section II presents digital twinning; Section III describes the cloudlet architecture used. Section IV presents the implementation of digital twinning of three sensors (accelerometer, gyroscope and Magnetometer) on the cloudlet systems. The experimental results of the digital twin implementation are shown in Section V, and Section VI concludes the paper and discusses the future direction of research.

II. DIGITAL TWINNING

[21] gives an overview of digital twin applications. Digital twins are used in different sectors. The sectors where digital twins are used are (a) manufacturing, (b) aerospace, (c) marine, (d) agriculture, (e) healthcare, and (f) mining. Digital twins can be used for the following purposes: (a) simulation, (b) monitoring, and (c) control. Simulations are used to model the behaviour of the system in virtual space. This allows optimization of the product or the production process. The monitoring includes current data so that the current state of the product or system can be interpreted. When used in control, digital twins can be used for predicting events and, based on the predictions, can control the behaviour of the product or system.

Another way to classify the digital twin is based on the physical device it is modelling. There are four categories of physical objects: (a) Manufacturing assets, (b) products, (c) infrastructure, and (d) Human [21]. A manufacturing asset refers to an object from a tool like a CNC machine [22]. Product – indicates a completed product. Infrastructure refers to bridges, cities, etc. [23]; in the case of humans, it could refer to an industry employee trained by a digital twin expert or an expert training the employees on a hazardous system [24].

The completeness of the digital twin in the number of features that are represented – for example, a digital twin of a room has parameters such as temperature, humidity, lighting, O2 Levels, occupancy, and power consumption and these parameters have to be continuously updated, so data is sent regularly. The digital twin of the room is updated in real-time.

A digital twin can be created before or after the physical object is created. If created before, it is used to analyze the behaviour, verify the various states and then build the physical object; such a digital twin is termed a proto-type twin [25]. If the twin is bound to the device later, it is called a digital twin instance [26]. A digital twin instance of any machinery in the industry can be used for predicting events, changes in states and failures due to real-time data sent from the machine to the digital twin.

The digital twin is the key technology for Industry 4.0; combined with Augmented Reality / Virtual Reality and IIoT, they provide valuable tools for manufacturing, training, health-care, and smart city environments. When writing this paper, we have been unable to find detailed developments that study and integrate these three technologies.

The digital twin can allow companies to have a complete digital footprint of their products from the conceptual phase to the design and development phase, the deployment and maintenance phase through the entire product life cycle. This allows the manufacturers to understand not only the product designed but also the system that built the product and the application of the product. With the creation of the digital twin, companies may be able to detect significant improvements in the areas of value in the areas (i) speed to market of a new product, (ii) improved operations, (iii) reduced defects, and (vi) analysis of emerging new business models to drive revenue. There are varying definitions of digital twin (a) one definition states that [27] "a digital twin is an integrated model of an as-built product that is intended to reflect all manufacturing defects and be continually updated to include the wear and tear sustained while in use." (b) another definition of the digital twin is [28] "as a sensor-enabled digital model of a physical object that simulates the object in a live setting."

To implement a digital twin, considerable processing power is required as huge volumes of high-speed data need to be analyzed continuously so that the behaviour of the digital twin exactly replicates the behaviour of the physical object and is also able to predict future falls or unpredictable states that the object may enter into, hence most digital twins are implemented in a cloud-based architecture. Due to the unsuitability of cloudlets-based architecture IIoT, as stated in section I, the following section describes a cloudlet architecture that IIoT systems can use. The example illustrated using the cloudlet architecture replicates the behaviour of multiple sensors and is described in detail in section IV.

III. CLOUDLET ARCHITECTURE

Cloudlets are designed to tackle the requirements of IoT and, at the same time, overcome the high latency issues associated with cloud computing. The solution provided by the cloud brings the computing resources closer towards the end device [29]. Cloud computing is flexible, scalable, and cost-effective while being resource-rich and globally accessible. The clouds may not be close to the user and may be connected via multiple switches and routers, which add to the network latency. Semi-urban and rural areas where there is limited infrastructure and connectivity, it may not be possible to use the available cloud resources optimally. An alternative would have been to use smartphones to process the data. Despite the evolution of processing powers, mobile phones have limited processing power and memory, have short battery life and have heat dissipation issues [30] [31].

To overcome the limitations of cloud computing, researchers generally go in for Edge computing. Cloudlets [32] [33] is a variant of Edge computing; the primary aim of cloudlets is to bring the capabilities, the services and the cloud applications closer to the Edge and, hence, to the users. The End–devices in the cloudlet systems are usually a single hop away [34].

Cloudlets, Edge and Cloud computing can be a part of a single hierarchical architecture, as shown in Figure 1. Cloudlets can be built using devices with average processing capabilities, such as SoCs. Rather than using a single powerful computing system, a distributed system of multiple SoCs can be combined to form small clusters that are portable. Like access points, it is also possible to deploy cloudlets at any location. It is also possible to combine multiple cloudlets to form a larger computing platform, thereby providing scalability and extendibility. As the cloudlet and the End device are one-hop neighbours, the communication latency is minimal while maximizing the bandwidth utilization and retaining the required quality of service.

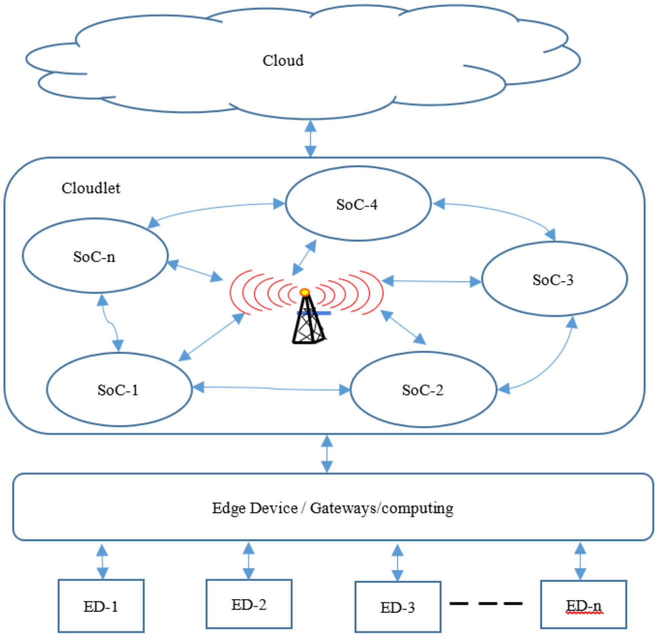


Fig. 1: Proposed Architecture of the Cloudlet system

The cloudlet system uses a distributed task scheduling and data distribution architecture described in our earlier work [35] [36]. We have also developed a custom network protocol stack that ensures minimum latency with minimum control overhead while maximizing the throughput. Initial experiments that we have conducted with this network protocol stack show no packet loss and negligible latency in terms of less than 0.1 microseconds. We are not describing the network protocol stack in this paper due to the limitation of space.

IV. IMPLEMENTATION OF DIGITAL TWINNING OF A SENSOR ON CLOUDLET SYSTEMS

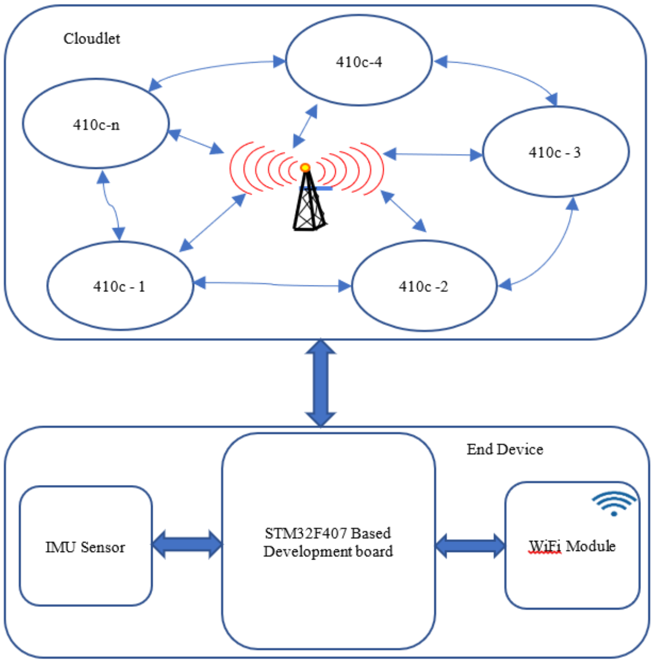


Fig. 2: Interface of the End-Device to the cloudlet system composed of multiple Qualcomm Snapdragon 410c

This section gives the experimental setup used for the implementation of the digital twining using a cloudlet system. Figure 2 gives the implementation architecture of the cloudlet system.

The cloudlet system was built using multiple Qualcomm Snapdragon 410c SoC. We varied the number of nodes in the cloudlet system from 4 to 25. The nodes in the cloudlet system are interfaced wirelessly using a minimal control overhead and minimal latency custom network protocol. The network protocol is embedded into the 410c SoCs. Also, the 410c SoCs are interfaced with the cloud when the volume of data is high. When the processing requirement reaches the peak that the cloudlet can no longer handle, it is migrated to the cloud. The cloud does long-term storage and data processing while the current data and the processing of the data take place on the cloudlet.

The sensors twined are the accelerometer, gyroscope and magnetometer. We have used MPU6500 [37], Which has a three-axis accelerometer and gyroscope, and GY271 [38], which is a magnetometer. Using these three sensors, it is possible to track the position of the spindle in the system and the rate at which it is rotating. We were able to produce an exact 3D replica of the rotational position while at the same time, displaying the values of the sensors.

The sensors were connected to STM-32F407 [39], which was the processing unit on the end–device. The actual end-

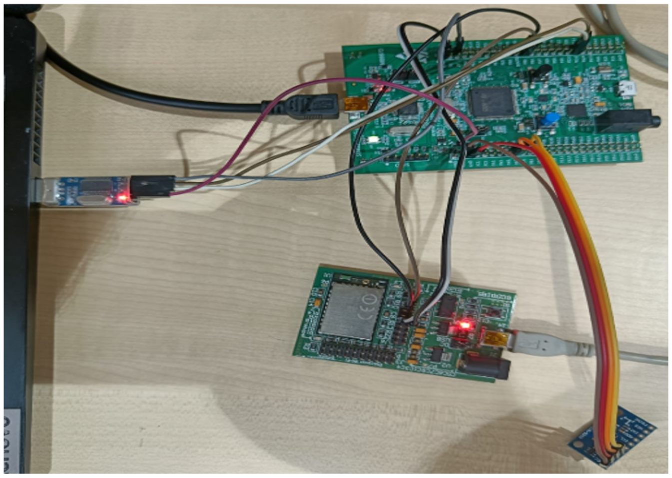


Fig. 3: Interfacing the End – device interfaced with the sensors and CC 2500.

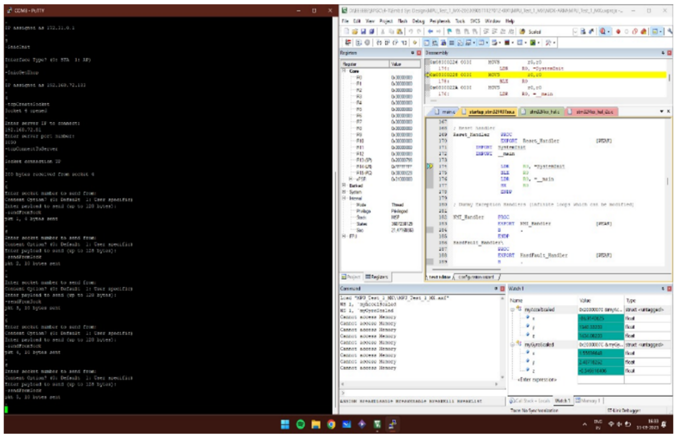
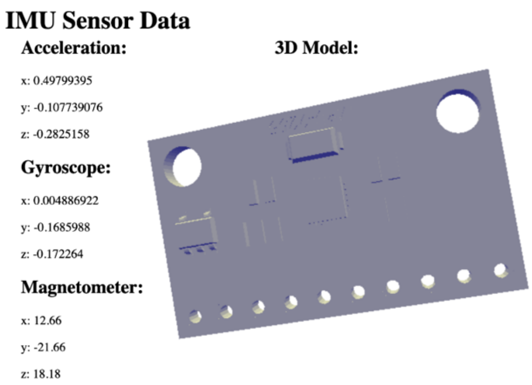


Fig. 4: Code and the data relayed to the SoC via CC2500.

device is shown in Figure 3. The data was sent to the 410c SoC, to which the end device was interfaced via a CC 2500 module [40]. The data was sampled at a rate of 20 Hz and was continuously sent to the 410c SoC with which it was interfaced on the cloudlet. Our distributed data storage algorithm ensured that the data was uniformly distributed among the various SoCs interfaced on the cloudlet. Once the data was received on the cloudlet, the tasks that were required to model the device and produce a 3D virtual image were invoked with every set of data. Figure 4 shows the code and the data relayed to the SoC via CC2500.

The CC2500 simply acts as a wireless transceiver and relays the data from the End device to the cloudlet. No specific protocol is used for interfacing the End device to the cloudlet. Currently, each end device has been allotted its own node in the cloudlet. In future, as the number of end devices increases while the cloudlet size remains the same, we plan to implement the same custom protocol used for communication between the nodes in the cloudlet to establish a link between the end device and any node in the cloudlet that is currently free.

V. EXPERIMENTAL RESULTS



IMU Sensor Data

Acceleration:

x: 0.49799395
y: -0.107739076
z: -0.2825158

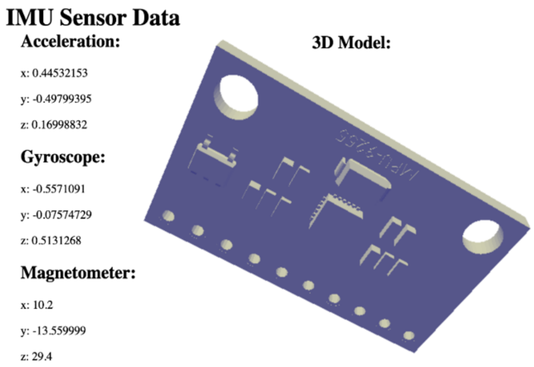
Gyroscope:

x: 0.004886922
y: -0.1685988
z: -0.172264

Magnetometer:

x: 12.66
y: -21.66
z: 18.18

Fig. 5: Digital twin based on sensor data-position a



IMU Sensor Data

Acceleration:

x: 0.44532153
y: -0.49799395
z: 0.16998832

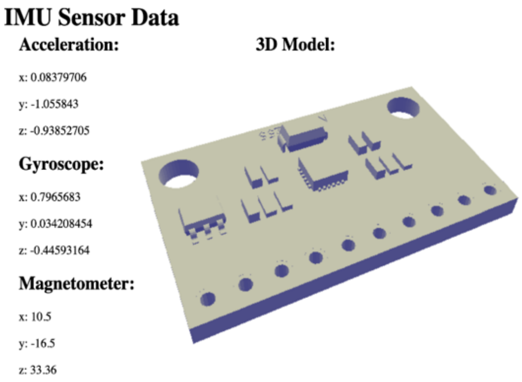
Gyroscope:

x: -0.5571091
y: -0.07574729
z: 0.5131268

Magnetometer:

x: 10.2
y: -13.559999
z: 29.4

Fig. 6: Digital twin based on sensor data-position b



IMU Sensor Data

Acceleration:

x: 0.08379706
y: -1.055843
z: -0.93852705

Gyroscope:

x: 0.7965683
y: 0.034208454
z: -0.44593164

Magnetometer:

x: 10.5
y: -16.5
z: 33.36

Fig. 7: Digital twin based on sensor data-position c

This section presents the results obtained when the sensors were twined. Figure 5, Figure 6 and Figure 7 shows the digital twin in various positions based on the sensor's data. The sensor positions depend on the accelerometer, gyroscope and magnetometer data, and there was no latency observed in between the variation of the physical position when compared to the virtual position. The task of converting the data into position and rendering it into a 3d image was done using seven 410c SoCs, of which only three were required to maintain a constant update in the sensor data and the update of the image. Even the three SoCs were not fully loaded but ran at less than 80%.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have presented an application of a cloudlet system which is used for the digital twinning of three different sensors. The three sensors could be used to give the position of the spindle, which is a part of multiple rotating machines that are used in the manufacturing industry. We were successfully able to implement the digital twin using a cloudlet system built with 410c SoC. In fact, we needed less than 80% CPU processing power of only three SoCs in the cloudlet system to implement the digital twin of the sensor and keep it updated at a sampling rate of 20 Hz. In future, we plan to digitally clone the entire machine and take the process further to cloning the entire control system built using multiple machines using the cloudlet system that we have developed using 410c. Augmented reality and virtual reality can be used to create a 3D interactive user interface, where the user can change multiple parameters and view the variations in the performance of the machine.

REFERENCES

[1] Boyes, H., Hallaq, B., Cunningham, J., & Watson, T. (2018). The industrial internet of things (IIoT): An analysis framework. Computers in industry, 101, 1-12.

[2] Munirathinam, S. (2020). Industry 4.0: Industrial internet of things (IIOT). In Advances in computers (Vol. 117, No. 1, pp. 129-164). Elsevier.

[3] Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2021). Upgrading the manufacturing sector via applications of industrial internet of things (IIoT). Sensors International, 2, 100129.

[4] Li, J., Maiti, A., Springer, M., & Gray, T. (2020). Blockchain for supply chain quality management: challenges and opportunities in context of open manufacturing and industrial internet of things. International Journal of Computer Integrated Manufacturing, 33(12), 1321-1355.

[5] Ijiga, O. E., Malekian, R., & Chude-Okonkwo, U. A. (2020). Enabling emergent configurations in the industrial internet of things for oil and gas explorations: a survey. Electronics, 9(8), 1306.

[6] Wu, Y., Dai, H. N., Wang, H., Xiong, Z., & Guo, S. (2022). A survey of intelligent network slicing management for industrial IoT: Integrated approaches for smart transportation, smart energy, and smart factory. IEEE Communications Surveys & Tutorials, 24(2), 1175-1211.

[7] Aziz, A., Schelén, O., & Bodin, U. (2020). A study on industrial IoT for the mining industry: Synthesized architecture and open research directions. IoT, 1(2), 529-550.

[8] Behera, S., Choubey, A., Kanani, C. S., Patel, Y. S., Misra, R., & Sillitti, A. (2019, April). Ensemble trees learning based improved predictive maintenance using IIoT for turbofan engines. In Proceedings of the 34th ACM/SIGAPP symposium on applied computing (pp. 842-850).

[9] Zhu, S., Ota, K., & Dong, M. (2021). Green AI for IIoT: Energy efficient intelligent edge computing for industrial internet of things. IEEE Transactions on Green Communications and Networking, 6(1), 79-88.

[10] Liu, Y., Yang, C., Huang, K., Gui, W., & Hu, S. (2022). A Systematic Procurement Supply Chain Optimization Technique Based on Industrial Internet of Things and Application. IEEE Internet of Things Journal, 10(8), 7272-7292.

[11] Sarkar, J. L., Ramasamy, V., Majumder, A., Pati, B., Panigrahi, C. R., Wang, W., ... & Dev, K. (2022). I-Health: SDN-based fog architecture for IIoT applications in healthcare. IEEE/ACM Transactions on Computational Biology and Bioinformatics.

[12] Mishra, A., Mohan, A., Mandal, A., Mohanty, A., & Chowdhury, A. (2022). Automation in Retail 'Follow-Me-Auto Shopping Cart': A Self-propelled Computer Vision-Based Shopper Following Cart with Auto-billing Feature Using IIoT. In Recent Advances in Manufacturing, Automation, Design and Energy Technologies: Proceedings from ICoFT 2020 (pp. 475-483). Springer Singapore.

[13] Wu, W., Zhao, Z., Shen, L., Kong, X. T., Guo, D., Zhong, R. Y., & Huang, G. Q. (2022). Just Trolley: Implementation of industrial IoT and digital twin-enabled spatial-temporal traceability and visibility for finished goods logistics. Advanced Engineering Informatics, 52, 101571.

[14] Frankó, A., Hollósi, G., Ficzere, D., & Varga, P. (2022). Applied Machine Learning for IIoT and Smart Production—Methods to Improve Production Quality, Safety and Sustainability. Sensors, 22(23), 9148.

[15] Qiuchen Lu, V., Parlikad, A. K., Woodall, P., Ranasinghe, G. D., & Heaton, J. (2019). Developing a dynamic digital twin at a building level: Using Cambridge campus as case study. In International Conference on Smart Infrastructure and Construction 2019 (ICSIC) Driving data-informed decision-making (pp. 67-75). ICE Publishing.

[16] Lins, R. G., & Givigi, S. N. (2021). Cooperative robotics and machine learning for smart manufacturing: Platform design and trends within the context of industrial internet of things. IEEE Access, 9, 95444-95455.

[17] Ding, X., Zhang, Y., Li, J., Mao, B., Guo, Y., & Li, G. (2023). A feasibility study of multi-mode intelligent fusion medical data transmission technology of industrial Internet of Things combined with medical Internet of Things. Internet of Things, 21, 100689. and Decision Making 11 (2011) 51.

[18] Urrea, C., & Benítez, D. (2021). Software-defined networking solutions, architecture and controllers for the industrial internet of things: A review. Sensors, 21(19), 6585.

[19] Michael Grieves, Origins of The digital twin Concept, 2016. 10.13140/RG.2.2.26367.61609.

[20] Manoj S Kakade, Anupama Karuppiah, Mayank Mathur, Manasi Bibekar, Gaurav Basu , Aaditya Raghavan, Ananth Raghav, Pranav Lekshminarayanan, Multitask Scheduling on Distributed Cloudlet System Built Using SoCs, Proceedings of the 27 th World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI 2023)

[21] Enders, M. R., & Hoßbach, N. (2019). Dimensions of digital twin applications-a literature review.

[22] Vichare, P., Nassehi, A., Kumar, S., & Newman, S. T. (2009). A Unified Manufacturing Resource Model for representing CNC machining systems. Robotics and Computer-Integrated Manufacturing, 25(6), 999-1007.

[23] Lu, Q., Parlikad, A. K., Woodall, P., Don Ranasinghe, G., Xie, X., Liang, Z., ... & Schooling, J. (2020). Developing a digital twin at building and city levels: Case study of West Cambridge campus. Journal of Management in Engineering, 36(3), 05020004.

[24] Longo, F., Padovano, A., De Felice, F., Petrillo, A., & Elbasheer, M. (2023). From "prepare for the unknown" to "train for what's coming": A digital twin-driven and cognitive training approach for the workforce of the future in smart factories. Journal of Industrial Information Integration, 32, 100437.

[25] Botín-Sanabria, D. M., Mihaita, A. S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. D. J. (2022). digital twin technology challenges and applications: A comprehensive review. Remote Sensing, 14(6), 1335.

[26] Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the digital twin: A systematic literature review. CIRP journal of manufacturing science and technology, 29, 36-52.

[27] Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2018). digital twin in industry: State-of-the-art. IEEE Transactions on industrial informatics, 15(4), 2405-2415.

[28] Evangeline, P. (2020). digital twin technology for "smart manufacturing". In Advances in Computers (Vol. 117, No. 1, pp. 35-49). Elsevier.

[29] Mohammad Babar; Muhammad Sohail Khan; Farman Ali; Muhammad Imran; Muhammad Shoaib; Cloudlet Computing: Recent Advances, Taxonomy, and Challenges; IEEE Access Vol:9 pp: 29609 - 29622 Feb 2021

[30] P. H. Raj, P. R. Kumar, and P. Jelciana, "Mobile cloud computing: A survey on challenges and issues," Int. J. Comput. Sci. Inf. Secur., vol. 14, no. 12, p. 165, 2016.

[31] D. Uma, S. Udhayakumar, L. Tamilselvan, and J. Silviya, "Client aware scalable cloudlet to augment edge computing with mobile cloud migration service," Int.J . Interact. Mobile Technol., vol. 14, no. 12, p. 165,Jul. 2020.

[32] L. Tamilselvan, “Client aware scalable cloudlet to augment edge computing with mobile cloud migration service,” Int.J . Interact. Mobile Technol., vol. 14, no. 12, p. 165, Jul. 2020.

[33] D. Uma, S. Udhayakumar, L. Tamilselvan, and J. Silviya, “Client aware scalable cloudlet to augment edge computing with mobile cloud migration service,” Int.J . Interact. Mobile Technol., 2020.

[34] F. Vhora and J. Gandhi, “A comprehensive survey on mobile edge computing: Challenges, tools, applications,” in Proc. 4th Int. Conf. Comput. Methodologies Commun. (ICCMC), Mar. 2020, pp. 49–55.

[35] Manoj Subhash Kakade, Anupama Karuppiah, Samarth Agarwal, Mudigonda Sreevastav, Obulreddigari Gayathri, V. Ranjith, Sista Kasi Vishwanath, and Gaurav Basu, Centralized Tasks Scheduling and Load Balancing on a Cloudlet Proceedings of Eighth International Congress on Information and Communication Technology, Lecture Notes in Networks and Systems 694, https://doi.org/10.1007/978-981-99-3091-3_37

[36] Manoj S Kakade, Anupama Karuppiah, Mayank Mathur, Priyansh Parikh, Raghav Dhir, Tejas Gokhale, Tasks Scheduling and Load Balancing on a Cloudlet system using Qualcomm 410c, Proceedings of the 26 th World Multi- Conference on Systemics, Cybernetics and Informatics (WMSCI 2022)

[37] MPU-6500 Product Specification Revision 1.3 2018 , TDK InvenSense [Accessed 10-Sep-2023] https://invensense.tdk.com/download-pdf/mpu-6500-datasheet/

[38] GY271 Datasheet ,Handson Technology , [Accessed 10-Sep-2023] https://handsontec.com/dataspecs/sensor/GY-271%20HMC5883L.pdf

[39] STM32F4DISCOVERY Databrief , ST Microelectronics [Accessed 10-Sep-2023] https://www.st.com/en/evaluation-tools/stm32f4discovery.html

[40] CC2500 Low-Cost Low-Power2.4GHz RF Transceiver datasheet , Texas Instruments [Accessed 10-Sep-2023] https://www.ti.com/lit/ds/symlink/cc2500.pdf/