Digital Twins for Smart Home Gadget Threat Prediction using Deep Convolution Neural Network

Mrs. Valluri Padmapriya, Dr. Muktevi Srivenkatesh
Department of Computer Science-GITAM School of Science, GITAM Deemed to be University,
Visakhapatnam, Andhra Pradesh, India

***Abstract*—Digital twin is one of the most important innovations in the Internet of Things (IoT) era and business disruption. Digital twins are a growing technology that bridges the gap between the real and the digital. Home automation in the IoT refers to the practice of automatically managing and monitoring smart home electronics by use of a variety of control system methods. The geysers, refrigerators, fans, lighting, fire alarms, kitchen timers, and other electrical and electronic items in the home can all be managed and monitored with the help of a variety of control methods. Digital twins replicate the physical machine in real time and produce data, such as asset degradation, product performance level that may be used by the predictive maintenance algorithm to identify the product functionality levels. The purpose of this research is to design the framework of Digital Twin using machine learning and state estimation algorithms model to assess and predict home appliances based on the probability rate of smart home system gadgets functionality. The main goal of this research is to create a digital twin for smart home gadgets that are used to monitor the health status of these devices for increasing the life time and to reduce maintenance costs. This research presents a Deep Convolution Neural Network based Logistic Regression Model with Digital Twins (DCNN-LR-DT) for accurate prediction of smart home gadget functionality levels and to predict the threats in advance. The proposed model is compared with the traditional models and the results represent that the proposed model performance is better than traditional models.**

Keywords—Digital twins; deep learning; convolution neural network; logistic regression; internet of things; smart home; IoT gadget functionality; threat prediction

I. Introduction

Modern industry and the country's economy depend critically on Industrial revolution 4.0 and smart manufacturing. Industry 4.0 intends to create a global networked infrastructure that addresses compatibility and interoperability problems within and between all levels of automated systems and factories, enhancing the agility and flexibility of manufacturing methods [1]. Advanced robotics, which acts as an agent acting that appears in every area of production lines, is equally essential to smart factory. Digital Twin (DT) is attracted increasing scientific attention as a result of the extensive research and development on Industry 4.0 and Artificial Intelligence (AI) [2]. The network and data serve as the foundation of DT as a digital representation of a physical object, the algorithm and modeling serve as the core, and the application and service serve as the application. The expenses of manufacturing businesses rise as a result, and at the same time, their organizational structures and operational procedures face enormous difficulties [3]. In light of this, AI-powered DT technology is anticipated to adapt conventional model-based techniques to changing boundary conditions and offer a demand-oriented, real-time competent evaluation basis to effectively assist decision-making in multi-objective challenges [4]. Numerous studies have already discussed and characterized DT from the standpoint of broader concepts and technology, as well as some sectors, without a specific focus on AI, such as product design, modelling and simulation, and problem diagnosis and prognostics [5]. Various engineering implementation scenarios pose unique problems [6]. The systematic and thorough integration of domain-specific knowledge is much more crucial for the foundation of DT and AI. In the context of the environment and circular economy, there is currently still a dearth of thorough industry-focused reviews of AI and DT technology.

The National Aerospace and Space Administration describes the idea of DT as an act involving, multiscale, statistical simulation that makes use of physical models, sensor feeds, fleet histories, etc. to mimic the twin's daily activities [7]. Any corporation can gain from having electronic information, and even an individual may value their data to the point that they simply cannot risk losing it. In recent years, the availability of low-cost sensors and open-source middle-ware software has opened up interesting research areas in the robotics field. In particular, the next generation of simulation models called DT [8], which represents a continuous virtual replica of physical systems, has gained increasing attention. It can be used to create a simulation of a smart home including assistive/service robots and human users. It has applications in the optimization of robots and smart home settings [9]. For example, finding the optimal number and configuration of sensors especially when new robots or users are introduced [10]. As another example, monitoring in real-time, further analysis and learning of edge cases and rare situations in DT for the safety of human users, e.g., by pushing those events from simulation to real-world and vice-versa. In practice, such optimization should be carried out over a variety of houses and users. The digital twin can be created in all scenarios [11]. The digital model and process is shown in Fig. 1.

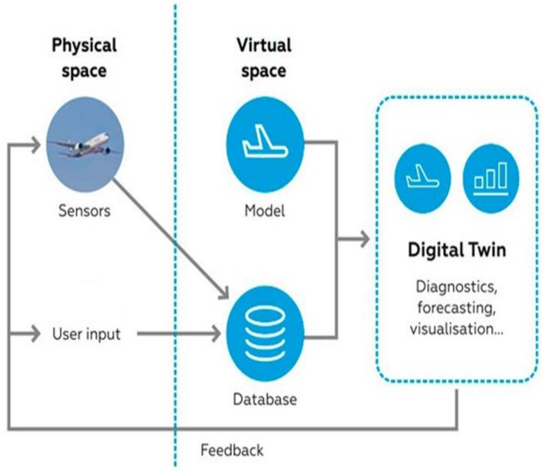

Fig. 1. Digital twin.

With the mounting deployments of the Internet of Things (IoT) systems, the significance of the concept of a digital illustration of physical things has gathered trivial interest in the recent years. Digital Twin is basically a living model of the physical skill or system, which will repeatedly adapt to changes in the milieu or operations and bring the best business outcome. It can also be rapidly, quickly and easily scaled for quick deployment for the other, similar applications [12]. Building a smart home is often an essence for deploying all the sensors, software, network, and physical assets. The data collected and analysis results are shared to the digital twin and can be monitored by an individual [13]. These digital proxies are expected to be built from the domain knowledge of subject matter experts as well as the real-time data collected from the devices [14]. Digital twin is the skill to craft a virtual depiction of the physical elements and the dynamics of how an IoT device operates and device act in response right through its lifecycle [15].

The IoT was motivating the design of digital twins so businesses could take action on data that crosses both the physical and digital worlds. Being able to see it, before DT is build, it has been a long-time aspiration for the manufacturing industry [16]. The technology called Digital Twins which makes it a reality. It allows users to understand how a product would perform before you build. Today’s proliferation of sensors, faster computing power and capturing data has grown exponentially [17]. The current acceleration in the usage of digital twins is mostly possible with the Internet of Things and the minor costs of technologies that boosted both IoT and digital twin. This illustrates how a digital twin route sensor generated data from an instrumented advantage and influences replication to forecast malfunction and make out in capabilities [18]. This makes possible an industry to take appropriate action to straight away to correct troubles and optimize the asset's recital [19]. Digital Twin is also called as a replica of an object; it's more than a blueprint or a schematic, virtual twins, shadows, and device virtualization. The process of digital twin creation is shown in Fig. 2.

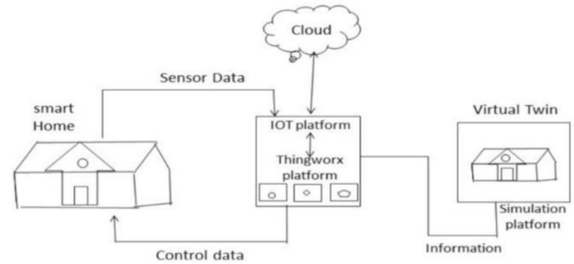

Fig. 2. Digital twin creation.

One of the most important technologies in the Fourth Industrial Revolution is the digital twin, a digital representation of a physical product, service, or production process. Because of the integration of the digital and physical realms, users may now proactively prevent issues through the study of data and the close observation of systems [20]. A digital twin design and system built on a common data standard are described in this research. It describes how to use edge devices, business intelligence, and realistic visualization to create a digital twin for integrated control monitoring [21]. The system's automated generation of digital twin models enables constant communication among field engineers for data collection, designers for modeling, and design engineers for layout changes [22]. As a result of this method, participants can better concentrate on their specific responsibilities in the creation of digital twins.

II. Literature Survey

Due to its critical role in maintaining the availability of several crucial services, the development of safety monitoring and management systems for Critical Infrastructures has attracted increasing attention and concern over the past few years. Due to the unique traits of these systems and the operators' innate reluctance to acts that can cause downtime, this task is difficult. Digital twins can offer a reliable environment for information security or evaluation of prospective mitigation methods to be used in response to certain conditions since they are accurate virtual replicas of physical items or processes. However, one’s on-premises implementation can be costly, implying a sizeable CAPEX for whom the return will currently rely on the capacity to intend and deploy an appropriate support infrastructure as well as implement efficient and scalable collection of data and processing mechanisms able to make use of the resources acquired. Sousa et al. [2] proposed an off-premises method for designing and deploying Digital Twins to protect critical infrastructures. In order to help the creation and testing of Machine Learning models to counteract security concerns like Denial-of-Service attacks, such Digital Twins are created utilizing real-time, highly accurate duplicates of Programming Logic Controllers. A significant portion of the predicted CAPEX for the on-premises model was converted like on, pay-as-you-go OPEX through the ELEGANT validation approach, which benefited from the functionality of the Fed4Fire federalized testbeds.

The World Wide Web's structure is comparable to that of the Digital Twin Web, which is made up of conceptual digital twins transmitted through Digital Twin Servers and documented as digital twin findings analyzed by Autiosalo et al. [3]. First before Digital Twin Web can be utilized effectively, standards must be developed; having an easily available server implementation that can encourage the creation of those standards. A Digital Twin Web host built on Git that is open-source and user-friendly is called Twin base. Twin base maintains digital twin papers in a repository, updates them using Git workflows, and then makes them accessible to users through a static web server. Users can view these documents using a library or a standard web browser. The browser interface allows for the free initialization of new server instances. Twin base was created using GitHub, Pages, and Actions, but it can be modified to accommodate different hosting options or self-hosting. To enable the development of derived and alternative server implementations, the author defined Twin base's fundamental architecture. The author offered the idea of a digital twin identity registry in order to answer the need for permanent, openly available, and transferable IDs for the Digital Twin Web. According to performance measurements, depending on the identification registry, the median reaction times for obtaining a digital twin file from Twin base was around 0.4 and 1.2 seconds.

Innovative solutions are required to assure the electrical system's resilience due to the rising frequency of cyberattacks on it. In order to establish a useful framework that can react to various threats on a collection of interconnected micro grids, this work leverages on the development in the Internet of Everything. In order to assure the cyber-physical system's efficient functioning, Saad et al. [6] offered a IoT-based DT of the system that communicates with the control system. The power cyber-physical and DT delivery over the IoT cloud is mathematically formulated. The proposed cybersecurity paradigm, in contrast to others in the literature, can lessen both solitary and group threats. The security protections are put into place utilising cloud computing, and the architecture was evaluated on a distributed system of control. Single-board computers are employed to implement the physical controllers.

In this study, Quan et al. [7] discussed the problem of binary classification for mixed static and dynamic data. The dynamic factors in the novel type of information vary over time and are captured at specific time points, like mixed numerical and categorical data. Due to the significant correlation in each variable caused by this discrete form, more shape and vary over time must be studied, necessitating the urgent need for an effective fusion model. To meet the challenge, the author suggested a novel fusion approach in which the separate findings from variables are converted to function f via grounds expansion, combined with barely changed via a combination logistic regression model and then the key features are chosen using a group grappling hook penalty term.

The goodness-of-fit criterion has been extensively utilised in the past to assess overall calibration of forecasts. The test aids in determining the significance of inaccurate predictions, which could point to model flaws. As data is created sequentially, the goodness-of-fit test, which is typically conducted at the conclusion of data collection, may not be able to identify changes in the woman's fit. In order to assess the goodness-of-fit at every time point and give an early warning if major changes take place during model fitting, Qiu et al. [8] looked at the possibilities for employing a new online gawd test.

Sharing data and information from various sources helps scientific partnerships, but maintaining privacy is a top priority. Concern over a possible privacy data leak is growing among researchers, sponsors, and the general public. In order to safeguard the storage and processing for sensitive information in a distributed setting, cutting-edge security techniques have been created. They do not, however, offer any security against information leaking from data analysis results performed by Kim et al. [11]. Studies on differential privacy, a cutting-edge paradigm for privacy protection, have addressed this issue with intriguing findings, but most of them need not be applicable to distributed scenarios. Combining privacy and security procedures is a logical answer to the issue, although simplistic approaches could produce subpar analytical results.

A digital replica of the actual system called as a DT is revolutionizing the way of life. Cyber-Physical Systems (CPS), the IoT, Big Data, Edge-Computing (EC), Artificial-Intelligence (AI), Machine Learning (ML), and other technologies were combined to create DT. DTs are created to improve a variety of applications in business, medicine, smart buildings, smart homes, etc. It's still in the early stages of development. By merging the substantial knowledge on technologies used in the development of DT in industrial and healthcare, this study fills in the gaps analyzed by Khan et al. [12]. The study of DT characteristics, tools and communication technologies used to create DT models, standards and reference models, as well as the researcher's current work in smart factory as well as healthcare, are the main topics of the paper.

A comprehensive range of sensors and actuators, as well as revealing abilities with high-level interface for realistic human contact, enable Pepper, a humanoid robot, to exhibit body language, perceive, and interact with its surrounding environment. In this paper, Cascone et al. [13] described experiences centered on the connection of the digital-twin with both the copies of the smart products in a smart home in order to present the creation of V-Pepper, the Pepper digital replica. Although Pepper robot has hands and arms, its motors and actuator are not strong enough to sustain lengthy testing sessions and training program to learn how to securely handle objects. Here, the metaphor of the digital twin is essential. Machine learning processes can be smoothly transferred to/from the digital-twin with a significant speedup, keeping the physical robot from degrading, by creating a virtual and trustworthy clone of the robot. The given case study provides an inspiration for ambient-assisted functioning in elder care as a practical application. The experience, along with the entire development and design process, has shown that VPepper and the smart cities offer intriguing potential for the physical correctness of the simulation and the accessibility of machine learning tools that may be translated and utilised for actual settings.

III. Proposed Method

Home automation includes the use of smart home applications. Instead of just saving power by turning things on and off, smart homes do a lot more [23]. Using these programs gives the impression that users are physically holding and manipulating the virtual things. Users explore using it for things like locking doors, turning off lights and fans, and even controlling the temperature in the fridge [24]. Depending on what users find most useful in the future, users can add on to the functionality of smart homes, transforming the surroundings into a more pleasant and stress-free place to live [25]. The safety and security of useful devices is paramount, and an automated system may help users feel at ease by alerting when to do things allowing users to control who has access to smart devices [26]. Many people find it tedious to constantly check their home gadgets about their working conditions and alerting users about the upcoming issues for hardware devices about their functionality [27].

The advent of digital twin technology can be traced to the development of both virtual technology and data collecting technology [28]. A digital twin is an identical copy of a physical object or person that exists in the real world. The connection and its digital counterpart have multiple possible implementations. Production management, manufacturing, healthcare, smart cities, and other fields all rely heavily on digital technology [29]. Currently, the primary focus of digital twin development is on optimising industrial production. Now that more data can be acquired because to advancements in communication and digitalization technologies, it's time to figure out how to put all that knowledge to good use. As a result, there is a lot of interest in, and momentum behind, the concept of digital twin. All physical entities, including humans, can have their functions monitored, understood, and optimised with the help of digital twins, which also provide constant feedback to enhance quality of life [30]. The ideal way to define a digital twin is as the seamless exchange of information between a real world machine and its digital counterpart. This research introduces the concept of a Digital Twin and explains how it can be applied in various house hold settings as well as the Internet of Things network for better functionality with extended lifetime.

In order to visualize the plans for the twin home, it is necessary to double-check that the planned physical system has successfully received data from sensors, stored it in a database, and run any necessary analytical procedures. An ecosystem was proposed to facilitate the interconnection of IoT devices and sensors, the exposition of the worth of IoT data, the creation of enterprise-level devices, and the authorization of end-users. As the go-between for the sensor and the digital information, and also as the home simulation model, a deep learning model is adopted. The digital duplicate was purpose-built to demonstrate its worth. To begin, a physical assertion is built into smart objects which use sensors to gather information on their current status, work environment, or location. All of the data collected by the sensors is transferred to a central system to be analyzed. This information is analysed in light of existing company metrics and other relevant context details. Environmental sensors monitor conditions and trigger responses according to those readings in order to cut down on power use and also raise alerts if any prior repair is required. Data collected by sensors revealed the extent to which resources were utilized. The proposed model framework is shown in Fig. 3.

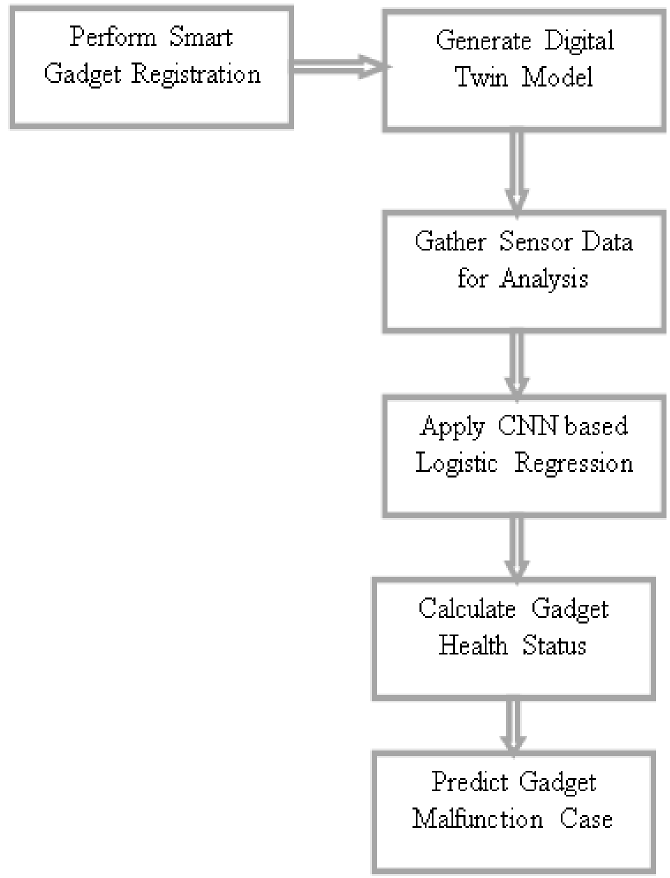

Fig. 3. Proposed model framework.

Digital twin concepts are used to outline a three-stage process for designing a smart home system. Plan, Construct, and Run. The process of making a Digital Copy to begin, a modelling software to produce a digital twin is used. A Digital Twin can be made in a few hours on a computer. Use software to make a virtual model of a Smart Home's infrastructure before constructing the real thing. The software we have here allows us to create a working model of the house. Optimizing device or system performance, reducing unscheduled downtime, and allowing engineers to digitally test solutions before physically repairing something are all possible with digital twins created in this research. The stage of design is critical. Using the IoT platform, the home was equipped with sensors, controllers, and actuators that are linked to a data acquisition component that takes data samples and provides insightful analytical results. This research presents a Deep Convolution Neural Network based Logistic Regression Model with Digital Twins (DCNN-LR-DT) for accurate prediction of smart home gadget functionality levels and to predict the threats in advance.

Algorithm DCNN-LR-DT

Step1:

Initially perform the smart gadget registration in the smart home for monitoring the devices performance. The smart gadget registration helps in creating a digital twin with a identity and the process of registration is performed in eq.1.

$$SGD[L] = \sum_{d=1}^{N} getGDaddr(d) + Node(ID) + TimStamp(getTime()) + Th \quad (1)$$

Here getGDaddr() is used to get the device logical address for further monitoring, Node(ID) represents the physical address to recognize the device and monitoring the malfunctions, Timestamp() is used to get the current time and Th is the threshold value considered. The Smart Gadget Health Status is shown in Fig. 4.

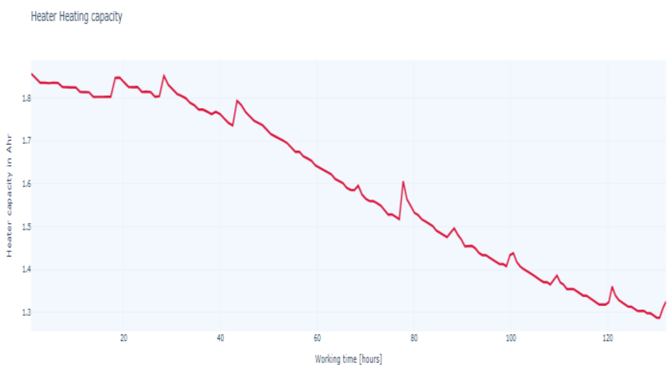

Fig. 4. Smart gadget health status.

Step2:

After registration of the gadgets, the digital twin identity is provided and the model generates an accurate digital twin model for gathering the data and analyzing the functionality of the gadget. The digital twin generation is performed in Eq. (2).

$$DigTwin(SGD(L)) = \sum_{d=1}^{M} getData\big(SGD(d)\big) + \sum_{d=1}^{M} \frac{F(setsimm(SGD(d))}{count(SGD(d))} \quad (2)$$

Here getData() is used to gather the sensor data and the setsimm() is used to create a simulation model of the gadget using the sensors for monitoring the device functionality. The comparison of physical model is shown in Fig. 5.

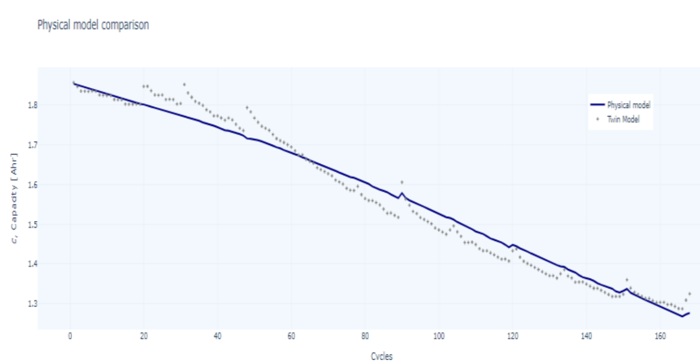

Fig. 5. Comparison of physical model.

Step3:

The sensor data is gathered by the central monitoring authority for analyzing the gadgets working process and malfunctions by the smart gadgets and the sensor data analysis is performed in Eq. (3).

$$CS(P) = \frac{\lambda + SGD_{avg} + \text{getsimm}(\text{SGD}(\text{d},\lambda)}{count(SGD) + \beta} + \sum_{d=1}^{M} getMax(SGD(d)) \quad (3)$$

β is the data interceptions from the sensors, that is the multiple data items collected. λ is the device functionality normal parameter that is set as fixed value. getMax() is used to get the device maximum attribute data for analyzing the device functionality.

Step4:

To identify the malfunctions in the device working process, CNN based Logistic Regression model is applied for analyzing a predicting the functionality as in Eq. (4) and Eq. (5).

$$LogReg\big(f(x)\big) = \frac{1}{1+e^{-(x-\mu)}} + \frac{1}{1+e^{-(\beta 0 - \beta 1 \mu)}} \quad (4)$$

$$MF\big(SGD(L)\big) = \sum_{d=1}^{L} \frac{dStat(LogReg(d))}{\lambda} + \delta\big(CS(d)\big) - \tau \quad (5)$$

μ is the location parameter of the gadget and x is the scaling attribute, β is the data interceptions from the sensors. λ is the device functionality normal parameter and τ is the noisy data gathered from the sensor. δ is the model used for highly correlated value set. The error rate between Physical Twin and Digital Twin is shown in Fig. 6.

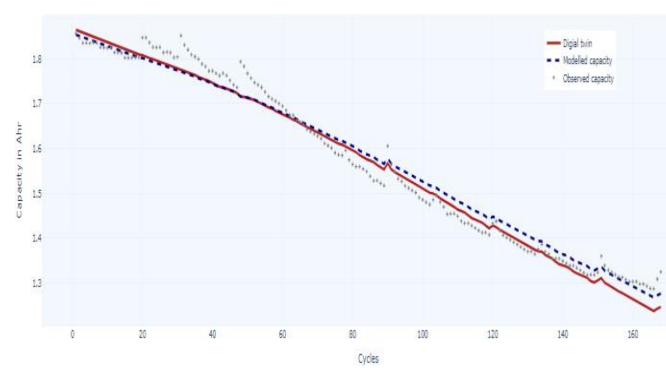

Fig. 6. Error rate between physical twin and digital twin.

Step5:

The gadget health status is calculated and updated to the user and the malfunction cause by the sensors is identified and the health status is calculated in Eq. (6).

$$\text{SGDHS}\big(\text{CS}(\text{M})\big) = \sum_{\text{d}=1}^{\text{M}} \lambda + \beta * \left(\text{maxattr}\big(\text{CS}(\lambda)\big) - \frac{\text{minattr}(\lambda)}{\tau}\right)^2 + \sum_{\text{d}=1}^{\text{M}} \lambda * \left(\tau - \frac{\beta * \text{CS}(\text{d})}{\text{count}(\text{MF})}\right)^2 \quad (6)$$

Done

IV. RESULTS

Digital twin is used to describe physical items that also include digital data. It is also thought of as a technology for symbolizing simulation techniques. The concept of a digital twin is related to other technologies such as cyber physical and digital shadow systems. The connection between these ideas has to be investigated. Designing, running, and repairing the product all make use of digital twin technology. Large volumes of data have been generated by these applications, necessitating a data analysis system for use in fault prediction and maintenance. It is possible to solve the issue with the help of digital twin technology, which acts as a connection between the real and virtual gadgets. Data is the lifeblood of the digital twin concept. Radio Frequency Identification (RFID) tags and readers consist of a variety of elements and sensors. These components are picked and combined so that the digital twin can collect comprehensive data. When it comes to transmitting data to a digital twin via central server, it can be challenging and expensive if the data in question comes in huge volumes and a wide variety.

Data-related technologies, such as data gathering, data mapping, data processing, and data transmission, vary widely depending on the specific use case. To make this data into a digital twin, standard data interfaces are needed. This research presents a Deep Convolution Neural Network based Logistic Regression Model with Digital Twins (DCNN-LR-DT) for accurate prediction of smart home gadget functionality levels and to predict the threats in advance. The proposed model is compared with the traditional Cloud-Based Digital Twinning for Structural Health Monitoring Using Deep Learning (CbDT-SHM) model. The proposed model is implemented in python and executed in Google Colab. The dataset is gathered from the link https://www.kaggle.com/datasets/prasannaakella/digital-twin-gadget-health. The results represent that the proposed model performance is efficient than the traditional models.

Equipment like sensors, gadgets, appliances, and other equipment that collect and share data via the web are examples of Internet of Things smart devices. Embedded with other Internet of Things gadgets, they are pre-programmed for certain uses. The smart gadgets in which digital twin will be created will be registered with the model for analysis. The Smart Gadget Registration Time Levels of the proposed and existing models are shown in Fig. 7.

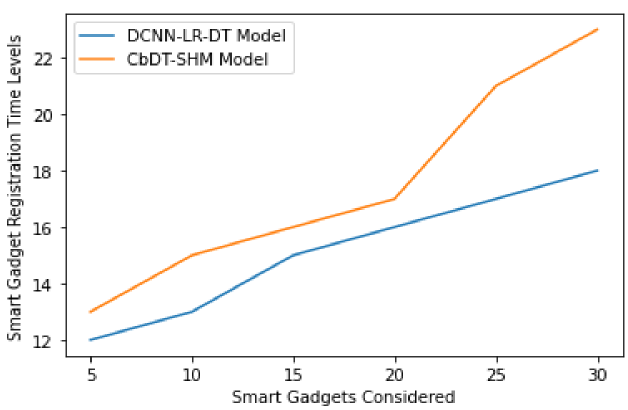

Fig. 7. Smart gadget registration time levels.

For a digital twin to be constructed, information about a physical item or process is needed so that an intangible model can be developed to replicate the actions and states of the physical one. Information collected throughout the product's lifetime may include design documents, production procedures, and engineering blueprints. The Digital Twin Setup Time Levels of the existing and proposed models are compared and the results are shown in Fig. 8.

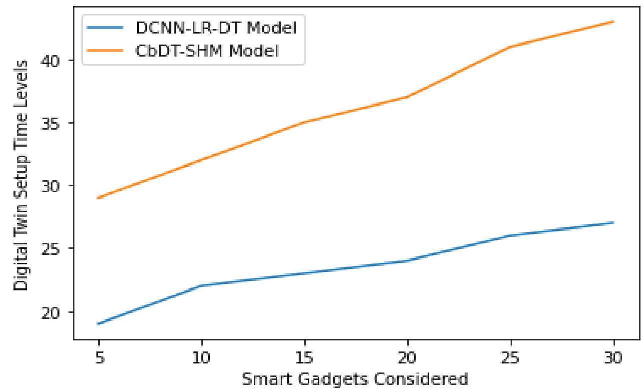

Fig. 8. Digital twin setup time levels.

A digital twin is a digital representation of the physical or system that extends its lifetime, is upgraded from real-time data, and employs simulation, advanced analytics and reasoning to support decision-making. The duplicate can be utilised alongside a prototype to provide input on the product's development or can serve as a model in its own right to mimic what may occur with a tangible version of the product after it is constructed. The accuracy levels of digital twin setup is shown in Fig. 9.

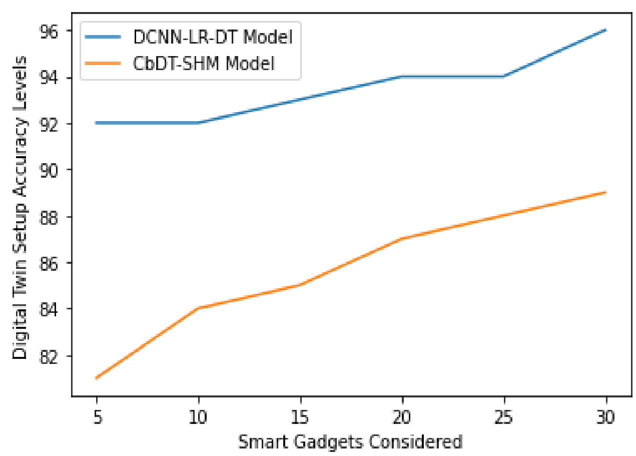

Fig. 9. Digital twin setup accuracy levels.

Data gathered through IoT sensors for processing. Anything from a home thermostat to a motor vehicle could be included in this category. The internet portion of IoT refers to the devices' ability to communicate with one another, share information, and transfer that information across networks for further processing. The sensor data gathered will be used for identification of smart devices working status. The Sensor Data Gathering Time Levels of the proposed and existing models are shown in Fig. 10.

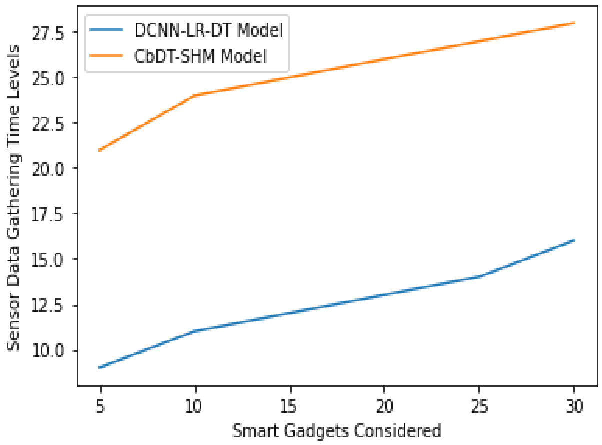

Fig. 10. Sensor data gathering time levels.

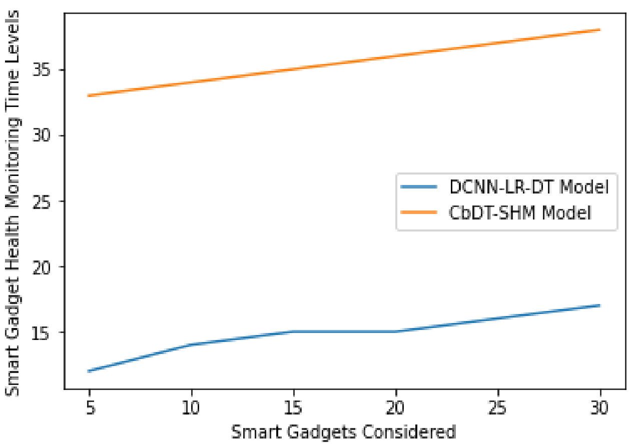

Fig. 11. Smart gadget health monitoring time levels.

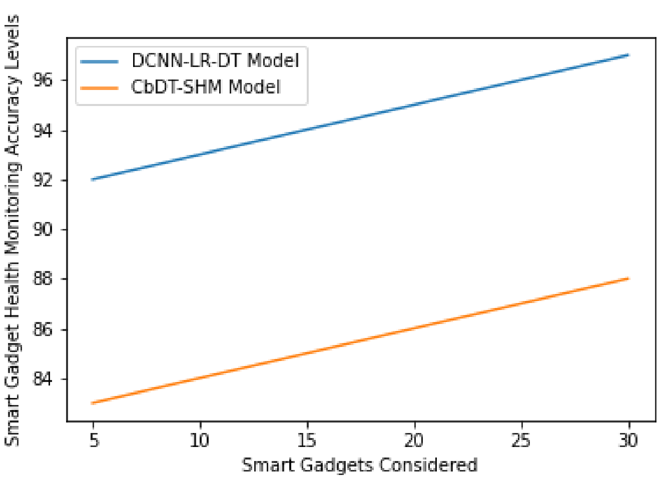

Fig. 12. Smart gadget health monitoring accuracy levels.

In essence, a digital twin is a living representation of a physical talent or system that can continually adjust to new conditions and operations to yield optimal results for the organization. It is also easy to scale up and deploy quickly for use with comparable applications. Deploying all of the sensors, software, networking, and physical assets is crucial to the construction of a smart building. The concept of a digital twin, or a continuous virtual reproduction of a physical system, has been gaining popularity. It can be used to simulate a smart house, complete with human occupants and robot helpers. Useful in optimizing robotic systems and even the comforts of a smart home for smart gadget health monitoring and suggesting the users for taking necessary actions for long life of gadgets. The Smart Gadget Health Monitoring Time Levels of the proposed and existing models are shown in Fig. 11 and the Smart Gadget Health Monitoring Accuracy Levels comparative results are represented in Fig. 12.

V. Discussion

The current study explores the potential of digital twins in predicting smart home gadget functionality levels and identifying threats in advance. The proposed model, based on a Deep Convolution Neural Network and Logistic Regression, achieved a high level of accuracy (97%) in identifying hardware risks of smart home gadgets. This study contributes to the growing interest in digital twin technology and its applications in the field of IoT. The results of this study suggest that digital twins can be a valuable tool in improving the efficiency and performance of smart home devices. By providing a virtual representation of physical objects, digital twins can monitor and optimize their functions. Moreover, digital twins can provide constant feedback to enhance the quality of life of individuals using smart home devices. Therefore, the implementation of digital twin technology in smart homes has the potential to significantly enhance the overall user experience.

VI. Conclusion

In the era of IoT and technological advancement, digital twins have emerged as a game-changing invention. The digital twin concept integrates and makes extensive use of cutting-edge technologies such as deep learning, machine intelligence, cloud services systems, big data configurations, software analytics, and the IoT, thereby radically altering IT business efficiency and lowering investment costs. The concept of a digital twin, which bridges the gap between real-world and digital environments, is gaining popularity. The advent of digital twin technology can be traced to the development of both virtual technology and data collecting technology. A digital twin is an identical copy of a physical object or person that exists in the real world. The connection and its digital counterpart have multiple possible implementations. Currently, the primary focus of digital twin development is on optimising industrial production. Now that more data can be acquired because to advancements in communication and digitalization technologies, it is time to figure out how to put all that knowledge to good use. As a result, there is a lot of interest in, and momentum behind, the concept of digital twin. All physical entities, including humans, can have their functions monitored, understood, and optimized with the help of digital twins, which also provide constant feedback to enhance quality of life. The ideal way to define a digital twin is as the seamless exchange of information between a real-world machine and its digital counterpart. This research presents a Deep Convolution Neural Network based Logistic Regression Model with Digital Twins model for accurate prediction of smart home gadget functionality levels and to predict the threats in advance. The proposed model is limited to check the health status of smart home gadgets. With a focus on various levels, the difficulties and future opportunities of Intelligence DTs in advanced robotics and smart manufacturing can be examined.

REFERENCES

[1] H. V. Dang, M. Tatipamula and H. X. Nguyen, "Cloud-Based Digital Twinning for Structural Health Monitoring Using Deep Learning," in IEEE Transactions on Industrial Informatics, vol. 18, no. 6, pp. 3820-3830, June 2022, doi: 10.1109/TII.2021.3115119.

[2] B. Sousa, M. Arieiro, V. Pereira, J. Correia, N. Lourenço and T. Cruz, "ELEGANT: Security of Critical Infrastructures With Digital Twins," in IEEE Access, vol. 9, pp. 107574-107588, 2021, doi: 10.1109/ACCESS.2021.3100708.

[3] J. Autiosalo, J. Siegel and K. Tammi, "Twinbase: Open-Source Server Software for the Digital Twin Web," in IEEE Access, vol. 9, pp. 140779-140798, 2021, doi: 10.1109/ACCESS.2021.3119487.

[4] M. Alqudah, M. Pavlovski, T. Dokic, M. Kezunovic, Y. Hu and Z. Obradovic, "Fault Detection Utilizing Convolution Neural Network on Timeseries Synchrophasor Data From Phasor Measurement Units," in IEEE Transactions on Power Systems, vol. 37, no. 5, pp. 3434-3442, Sept. 2022, doi: 10.1109/TPWRS.2021.3135336.

[5] M. Yaseliani, A. Z. Hamadani, A. I. Maghsoodi and A. Mosavi, "Pneumonia Detection Proposing a Hybrid Deep Convolutional Neural Network Based on Two Parallel Visual Geometry Group Architectures and Machine Learning Classifiers," in IEEE Access, vol. 10, pp. 62110-62128, 2022, doi: 10.1109/ACCESS.2022.3182498.

[6] A. Saad, S. Faddel, T. Youssef and O. A. Mohammed, "On the Implementation of IoT-Based Digital Twin for Networked Microgrids Resiliency Against Cyber Attacks," in IEEE Transactions on Smart Grid, vol. 11, no. 6, pp. 5138-5150, Nov. 2020, doi: 10.1109/TSG.2020.3000958.

[7] M. Quan, "An Advanced Hybrid Logistic Regression Model for Static and Dynamic Mixed Data Classification," in IEEE Access, vol. 10, pp. 73623-73634, 2022, doi: 10.1109/ACCESS.2022.3187767.

[8] Y. Qiu, L. Liu, X. Lai and Y. Qiu, "An Online Test for Goodness-of-Fit in Logistic Regression Model," in IEEE Access, vol. 7, pp. 107179-107187, 2019, doi: 10.1109/ACCESS.2019.2927035.

[9] D. Zhang, E. Stewart, J. Ye, M. Entezami and C. Roberts, "Roller Bearing Degradation Assessment Based on a Deep MLP Convolution Neural Network Considering Outlier Regions," in IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 6, pp. 2996-3004, June 2020, doi: 10.1109/TIM.2019.2929669.

[10] Z. Zhang and Y. Han, "Detection of Ovarian Tumors in Obstetric Ultrasound Imaging Using Logistic Regression Classifier with an Advanced Machine Learning Approach," in IEEE Access, vol. 8, pp. 44999-45008, 2020, doi: 10.1109/ACCESS.2020.2977962.

[11] M. Kim, J. Lee, L. Ohno-Machado and X. Jiang, "Secure and Differentially Private Logistic Regression for Horizontally Distributed Data," in IEEE Transactions on Information Forensics and Security, vol. 15, pp. 695-710, 2020, doi: 10.1109/TIFS.2019.2925496.

[12] S. Khan, T. Arslan and T. Ratnarajah, "Digital Twin Perspective of Fourth Industrial and Healthcare Revolution," in IEEE Access, vol. 10, pp. 25732-25754, 2022, doi: 10.1109/ACCESS.2022.3156062.

[13] L. Cascone, M. Nappi, F. Narducci and I. Passero, "DTPAAL: Digital Twinning Pepper and Ambient Assisted Living," in IEEE Transactions on Industrial Informatics, vol. 18, no. 2, pp. 1397-1404, Feb. 2022, doi: 10.1109/TII.2021.3090363.

[14] R L Zhao D X Yan Q Liu J W Leng F Wan J X Chen et al. "Digital twin-driven cyber-physical system for autonomously controlling of micro punching system" IEEE Access vol. 7 pp. 9459-9469 2019.

[15] M. Fahim, V. Sharma, T. -V. Cao, B. Canberk and T. Q. Duong, "Machine Learning-Based Digital Twin for Predictive Modeling in Wind Turbines," in IEEE Access, vol. 10, pp. 14184-14194, 2022, doi: 10.1109/ACCESS.2022.3147602.

[16] Y. Wu K. Zhang and Y. Zhang "Digital twin networks: A survey" IEEE Internet Things J. vol. 8 no. 18 pp. 13789-13804 Sep. 2021.

[17] L. Lei G. Shen L. Zhang and Z. Li "Toward intelligent cooperation of UAV swarms: When machine learning meets digital twin" IEEE Netw. vol. 35 no. 1 pp. 386-392 Jan. 2021.

[18] J. Lopez J. E. Rubio and C. Alcaraz "Digital twins for intelligent authorization in the B5G-enabled smart grid" IEEE Wireless Commun. vol. 28 no. 2 pp. 48-55 Apr. 2021.

[19] W. Sun H. Zhang R. Wang and Y. Zhang "Reducing offloading latency for digital twin edge networks in 6G" IEEE Trans. Veh. Technol. vol. 69 no. 10 pp. 12240-12251 Oct. 2020.

[20] Y. Lu X. Huang K. Zhang S. Maharjan and Y. Zhang "Communication-efficient federated learning for digital twin edge networks in industrial IoT" IEEE Trans. Ind. Informat. vol. 17 no. 8 pp. 5709-5718 Aug. 2021.

[21] P. Franco, J. M. Martínez, Y. -C. Kim and M. A. Ahmed, "IoT Based Approach for Load Monitoring and Activity Recognition in Smart Homes," in IEEE Access, vol. 9, pp. 45325-45339, 2021, doi: 10.1109/ACCESS.2021.3067029.

[22] N. M. Allifah and I. A. Zualkernan, "Ranking Security of IoT-Based Smart Home Consumer Devices," in IEEE Access, vol. 10, pp. 18352-18369, 2022, doi: 10.1109/ACCESS.2022.3148140.

[23] M. Wazid, A. K. Das, V. Odelu, N. Kumar and W. Susilo, "Secure Remote User Authenticated Key Establishment Protocol for Smart Home Environment," in IEEE Transactions on Dependable and Secure Computing, vol. 17, no. 2, pp. 391-406, 1 March-April 2020, doi: 10.1109/TDSC.2017.2764083.

[24] M. Marcos Amoroso, R. Moraes, G. Medeiros de Araujo and V. Silva Rodrigues, "Wireless Network Technologies for Smart Homes: A Technical and Economic Analysis," in IEEE Latin America Transactions, vol. 19, no. 5, pp. 717-725, May 2021, doi: 10.1109/TLA.2021.9448285.

[25] M. Khan, J. Seo and D. Kim, "Real-Time Scheduling of Operational Time for Smart Home Appliances Based on Reinforcement Learning," in IEEE Access, vol. 8, pp. 116520-116534, 2020, doi: 10.1109/ACCESS.2020.3004151.

[26] S. Chadoulos, I. Koutsopoulos and G. C. Polyzos, "Mobile Apps Meet the Smart Energy Grid: A Survey on Consumer Engagement and Machine Learning Applications," in IEEE Access, vol. 8, pp. 219632-219655, 2020, doi: 10.1109/ACCESS.2020.3042758.

[27] R. Minerva G. M. Lee and N. Crespi "Digital twin in the IoT context: A survey on technical features scenarios and architectural models" Proc. IEEE vol. 108 no. 10 pp. 1785-1824 Oct. 2020.

[28] O. E. Marai T. Taleb and J. Song "Roads infrastructure digital twin: A step toward smarter cities realization" IEEE Netw. vol. 35 no. 2 pp. 136-143 Mar./Apr. 2021.

[29] D. Mitchell et al., "Symbiotic System of Systems Design for Safe and Resilient Autonomous Robotics in Offshore Wind Farms," in IEEE Access, vol. 9, pp. 141421-141452, 2021, doi: 10.1109/ACCESS.2021.3117727.

[30] H. Gong, T. Rooney, O. M. Akeyo, B. T. Branecky and D. M. Ionel, "Equivalent Electric and Heat-Pump Water Heater Models for Aggregated Community-Level Demand Response Virtual Power Plant Controls," in IEEE Access, vol. 9, pp. 141233-141244, 2021, doi: 10.1109/ACCESS.2021.3119581.