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Intelligent Retrofitting Paradigm for Conventional Machines towards the Digital Triplet Hierarchy

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Abstract: Industry 4.0 is evolving through technological advancements, leveraging information technology to enhance industry with digitalisation and intelligent activities. Whereas Industry 5.0 is the Age of Augmentation, striving to concentrate on human-centricity, sustainability, and resilience of the intelligent factories and synergetic industry. The crucial enhancer for the improvements accomplished by digital transformation is the notion of 'digital triplet D3', which is an augmentation of the digital twin with artificial intelligence, human ingenuity, and experience. digital triplet D3 encompasses intelligent activities based on human awareness and the convergence among cyberspace, physical space, and humans, in which Implementing useful reference hierarchy is a crucial part of instigating Industry 5.0 into a reality. This paper depicts a digital triplet which discloses the potency of retrofitting a conventional drilling machine. This hierarchy included the perceptive level for complex decision-making by deploying machine learning based on human ingenuity and creativity, the concatenated level for controlling the physical system's behaviour predictions and emulation, the observing level is the iterative observation of the actual behaviour of the physical system using real-time data, and the duplicating level visualises and emulates virtual features through physical tasks. The accomplishment demonstrated the viability of the hierarchy in imitating the real-time functionality of the physical system in cyberspace, an immaculate performance of this paradigm. The digital triplet's complexity was diminished through the interaction among facile digital twins, intelligent activities, and human awareness. The performance parameters of the digital triplet D3 paradigm for retrofitting were eventually confirmed through appraising, anomaly analysis, and real-time monitoring.

Keywords: digital triplet; digital twin; digital retrofitting; cyber–physical system; cyber security; industrial automation; artificial intelligence; Industry 5.0

Citation: Alimam, H.; Mazzuto, G.; Ortenzi, M.; Ciarapica, F.E.; Bevilacqua, M. Intelligent Retrofitting Paradigm for Conventional Machines towards the Digital Triplet Hierarchy. *Sustainability* **2023**, *15*, 1441. https://doi.org/10.3390/su15021441

Academic Editors: Ki-Il Kim, Jinsoo Jang and Paulo Peças

Received: 28 October 2022
Revised: 18 December 2022
Accepted: 4 January 2023
Published: 12 January 2023

1. Introduction

The shift from the conventional industrial system to Industry 4.0 has the potential to auspiciously improve a variety of aspects, from potency to securely guarded manufacturing. Industry 4.0, often known as the Fourth Industrial Revolution, is a clear manifestation of the logical expansion of the intelligent prospect in the Third Industrial Revolution. One of the key features of the Fourth Industrial Revolution is the widespread adoption of cyber–physical systems, of which the Industrial Internet of Things (IIoT) is emerging as the central backbone construct. The concept of "the Internet of Things" (IoT) was born within specialised industrial applications of IoT's generic technologies [1,2]. With the goal of improving the effectiveness of automation and control processes, it will be necessary to make use of smart machinery that is technologically futuristic and has an elevated level of digitalisation and synchronous communications [3–5].

Utilising new technologies such as IoT or CPS to improve industrial systems and enhance process quality and safety through the product life cycle paves the way for additional challenges, such as cybersecurity issues, cloud computing, big data analysis, smart decision-making strategy, and enhancing the intelligent activity layer that involves the use of machine-learning modules in both virtual and physical worlds. To tackle those challenges, small and medium-sized enterprises have encountered several complications in implementing Industry 4.0, and many companies may not be able to afford a significant replacement for the antiquated industrial system while adapting the obsolete machinery to smart technologies at the same time [6,7]. Incidentally, the ultimate focus of Industry 4.0 is to diminish the dependence on human operators and increase focus on automation solutions; this is true, albeit Industry 4.0 is not yet completely cultivated and is still the key revolution towards digitalisation and smart manufacturing solutions in manufacturers' visions. On the contrary, the new breakthrough paradigm known as Industry 5.0 merges the complementary features of CPPS and human awareness to produce synergistic production environments [8–15]. Industry 5.0—also known as the "Age of Augmentation", considered the imminent era for the next industrial revolution, commits to integrating human ingenuity, experience, and awareness with smart machines to accomplish user-preferred production solutions [13,14]. Derived from the notions of the Fifth Industrial Revolution Industry I 5.0, and with respect to the annotation assigned by the European Economic and Social Committee, Industry I 5.0 must divergeadjust the strengths to tailor synergetic factories of the future by integrating human awareness with artificial intelligence and cyber–physical production systems (CPPS) [11,15].

Cyber–physical systems are quickly becoming the industry standard as automation and digitalisation technology evolve close to the industrial revolution of Industry 4.0 and the evolution of Industry I 5.0 [16]. The realisation of what is known as a digital twin is the primary benefit offered by such developed CPS systems, distinguished by integrating the physical configuration with their respective digital counterparts. This notion of digitisation is an improvement on the conventional Production Life-cycle Management (PLM) system that is used to comprehensively oversee the product's manufacturing process from the first leg of the design to the twilight of the distribution period in the market [17,18]. Product life-cycle simulation, predictive maintenance, anomalies detection, and process design optimisation are just a few of the applications where the use of cyber–physical systems can be seen, in which the common target of the main disciplines in manufacturing and industrial automation is to improve productivity and efficiency by deploying digital twins [19,20]. The use of digitalisation technologies enabled virtual activities through manufacturing and process planning. The several resulting physical assets are rehabilitated, retrofitted, and developed by providing a more direct integration and synchronisation from the physical to the virtual world; in addition, a large amount of data are processed, analysed, and evaluated by simulation-based planning and optimisation paradigms in order to make them available for real-time synchronisation and intelligent planning and decision making [20,21]. Although the digital twin has been defined as a simulation solution for planning and optimisation [22,23], the concept of the digital twin has exceeded its limitations as a virtual replica and probabilistic simulation of physical assets, and its integration levels are comprehensively deployed among all levels of the Industry 4.0 pyramid. However, the digital twin concept will keep its originality without utilising intelligent activities with machine-learning and artificial intelligence solutions [24–26]. Contrary to the ultimate intention of Industry I 5.0, the comprehensive advantages of human–machine interaction can be achieved by optimising human–machine integration to capitalise on the privilege of humans' decision-making abilities to systematically synchronise the efficiency of humans and machines. Hence, sophisticated HMI systems that combine more intelligent machinery and human productivity capacities are required, in which the intelligent digital twin is regarded as one of the essential technologies to enhance the interaction between humans and machines by comprising intelligent activities and machine imitation and emulation and integrating human awareness and experience for complex decision making and problem-solving [11–15]. In the literature, both low-level information fusion and high-level knowledge management have seen the incorporation of automated detection and diagnostics and human-contributed knowledge [27]. Furthermore, digital transformation aided human integration in cyber–physical environments in order to create more successful sociotechnical systems, including human skills and Tangail knowledge, by promoting techniques and technological solutions that encourage personnel involvement within technological systems in ways that use or intensify their cognitive capabilities [28,29].

Furthermore, contemporary industrial automation research endeavours are dedicated to consolidating system performance utilising artificial intelligence and machine learning. Several surveys have been conducted that revealed how data fusion and machine learning are gaining traction in many industrial sectors. Those surveys conveyed that the intelligent activity layer is the summit of the distinct four concatenation levels of the digital twin [30–32]. To identify the distinguishing feature of the intelligent digital twin and its control policy for complex decision-making, artificial intelligence and machine learning based on human-awareness approaches will be availed to improve the performance of the digital twin hierarchy, which culminates in what is known as a "digital triplet D3" [24–26,33].

To sustain the evolved digitisation in the traditional and future industrial environments, as well as to achieve the proposed smart manufacturing solution and exert significant optimisation activities with machine-learning approaches, responsible developers and engineers must be aware of potential threats to the technical development as well as the retrofitting requirements.

Nevertheless, the performance of decrepit utilities can be improved to its full potential by performing retrofitting, which improves the assets' reliability, flourishing in Industry 4.0, energy consumption, level of safety, maintainability, and flexibility. The concept of "smart retrofitting" is one that is discussed within the framework of "Industry 4.0". In addition to the traits that are typical of retrofitting, smart retrofitting embraces deploying crucial technologies that are disclosed by Industry 4.0 [34]. The demand for higher levels of productivity, sustainability, and technological sophistication is tied to the intervention of retrofitting. The incorporation of older factories into Industry 4.0 is made possible by utilising retrofitting, and by intrinsically attached smart manufacturing.

As proof of the notions of smart retrofitting and digital triplet D3, this paper contrives to develop a digital retrofitting paradigm based on the digital triplet hierarchy for a traditional drilling machine. Utilising a review of the relevant research [20–25] on the intelligent paradigm of the digital twin and the ontological framework of the digital triplet, the evaluation and elaboration of the digital triplet D3 hierarchy are classified.

The residual portion of this work is structured as follows. Section 2 annotates the research motivation and a review of the literature on prior digital retrofitting initiatives, the evolution of digital twin paradigms, and the innovative notions of Digital triplet 'D3'. In Section 3 we propose the ontology for digital triplet D3 hierarchy. Section 4 demystifies the integration between the digital twin and intelligent activities through the digital threads and the design of the digital triplet paradigm for retrofitting of Drilling Machine. Section 5 depicts the proposed paradigm's outcomes and discussion. Ultimately, Section 6 concludes the paper.

2. Research Motivation and Literature Review

2.1. Research Motivation

Although it is indisputable that digital transformation technology epitomises a cardinal role in smart manufacturing and the factories of the future, it can be challenging to integrate this technology into conventional industrial sectors. It is possible that expensive "integrated" industrial automation controllers such as the programable logic controller, 'PLC', Distributed Control Systems, 'DCS', in addition to exorbitant subscriptions to licensed and closed-source software packages could be the source of elevated levels of financial risk. While these programs comprehensively fulfil a wide range of needs, they encompass features that the user has no experience in or competencies in using.

The academic community disputes that the widespread adoption of technologies associated with Industry 4.0 is contingent on there being available low-cost and powerful IoT devices [6,7,20]. These devices are anticipated to assist mitigate the financial risk associated with testing out new digital technologies that could implement in digital retrofitting the SMEs in order to cultivate the digital twin paradigms by deploying intelligent activities, accomplishing the advanced level of the smart cyber–physical system, and optimising the efficiency of human–machine interactions in which machines assist and enhance workers rather than eliminate them; this will revitalise industries and pave the way for the industries' resilience and flourishing with Industry I5.0, which is dedicated to tailoring human-centric industry and sustainability and making Industry I 5.0 a reality [11–15].

As a result, the purpose of this research is to design a facile intelligent digital twin based on the digital triplet 'D3' hierarchy that makes use of low-cost microcontrollers and instigates that the digital twin is kept up to date in real-time by utilising sensor data from the physical counterpart.

The proposed digital triplet paradigm for retrofitting the conventional drilling machine-facilitated real-time monitoring, control, authentication, and optimisation of the system, as well as enhanced decision-making for anomaly detection, which was influenced by aggregating the cyber–physical system with AI and employing human ingenuity and creativity. The Arduino Mega and Node Js open-source platforms were employed to create an intelligent cyber model of the affordable intelligent retrofitting paradigm. Following the design, the physical system was built and programmed to perform standard machining functions. The socket IO real-time, bi-directional communication protocol was then deployed to establish interaction between the virtual and physical models. Authentication was accomplished with a camera and an Android App to augment the cyber security capabilities within the system's cyber counterpart. In addition to the standard control, automation, and real-time monitoring, the paradigm performance parameters were eventually confirmed through appraising and anomaly analysis.

2.2. Literature Review

2.2.1. From Industry 4.0 to Industry 5.0

Industry 4.0 introduces the notion of integrating automation into manufacturing industries through the use of electronics and information technologies (IT). In Industry 4.0, the advancement of pillar technologies such as big data analytics, digital twins, the Internet of Things (IoT), and cloud computing, in conjunction with Artificial Intelligence (AI), are used to facilitate the realisation of Smart Cyber–Physical Systems (CPS), which serve as a real-time interface between the virtual and physical worlds and provide on-demand services with high reliability, scalability, and availability in a distributed environment [1,35].

Industry 4.0 aspires to reinvent product manufacturing in order to create smart factories of the future that are more creative, cost-effective, and responsive to customer needs [6,7,35]. As a result, providing distinctive features at scale is one of the most desired competencies in Industry 4.0. Empowering Industry 4.0 capabilities entails a digital representation of every physical asset. Mirroring virtual models of physical assets can add significant value to the solution of complicated business problems. Furthermore, because of the absence of convergence between physical and cyberspace, data diminish in the product lifecycle, resulting in a poor level of efficiency and sustainability. Despite the success of Industry 4.0, the primary focus of Industry 4.0 is a technology-driven industrial paradigm transformation, with less attention paid to human factors and society. One source of anxiety about this industrial revolution is the potential for redundancies and job security as autonomous manufacturing systems become more prevalent. Consequently, the start of a new era of industrial transformation is imminent. This new era will avail engineers to fully utilise smart technical landscapes to serve humanity while also socialising factories. The human and societal issues throughout the industrial shift resulted in the birth of Industry 5.0. Industry 5.0 is a philosophical notion that looks to the future of the industry from the perspective of a human-centric, sustainable, and resilient manufacturing system [11–16].

I5.0, with its adaptable and flexible technology, is quick to act, resilient, and respectful of the planet's constraints while nurturing talent, diversity, and empowerment. according to Michael Rada, the pioneer and leader of the Industry 5.0 organisation, Industry 5.0 is the first industrial revolution driven by a human and is focused on the concepts of industrial upcycling (recognise, reconsider, realise, reduce, reuse, and recycle), claiming that in the industry, the workers and machines collaborate to boost process efficiency by leveraging human ingenuity and brainpower through workflow integration with intelligent systems to enable smooth communication between humans and CPPS enablers in the Social Smart Factory. Triggered by the ongoing digital transformations, the development of I 5.0 is evoked by data-based technologies such as the Industrial Internet of things (IIoT), AI, 5G, digital twin, cyber security and blockchains [15,16]. However, many digitalisation technologies, are still not widely used. This is especially true in SMEs and across entire value chains. Moreover, there is a lack of maturity and lack of standardisation in innovation management and R&D spending, especially in SMEs and traditional industry sectors. Thus, how can we link Industry 5.0 in the context of digital retrofitting? To transfer digitalisation to the SME, this paper aimed at filling this gap by providing a paradigm for understanding the implications of intelligent retrofitting based on the digital triplet paradigm towards Industry 5.0.

2.2.2. Retrofitting Approaches

Retrofitting entails integrating obsolete industrial systems with IoT solutions and artificial intelligence prerequisites, assisting them in embarking upon IoT technology, and can be referred to as "IoTization" [36]. The most difficult challenge of a retrofitting project is that an obsolete industrial system and SMEs are the most susceptible to being left behind in the I4.0 development [37], and equipment from different technical eras has distinct communication protocols [38,39]. On the other hand, because of a paucity of advanced sensors and actuators, further strenuous considerations must be determined before initiating a retrofitting project with a particular system. The most imperative ones are the contemporary system's digital consciousness, the condition of the machinery, and the performance requirement that determines the type of connectivity. Digital retrofitting [38–45], also known as Brownfield development [37], is an IoT upgrade that improves the utilisation of existing infrastructure with legacy equipment and software. These two definitions, according to some authorities, can be employed alternatively [40]. In this context, the overwhelming majority of the articles that were reviewed made use of smart retrofitting to provide predictions regarding the outcomes of developed assets. By involving the implementation of all necessary apparatuses and technology provided by Industry 4.0, the retrofitting purpose is to retain predictive maintenance activities by initiating the influence of a virtual model of the physical counterpart and mitigating high-risk incidents for both the technicians and industrial assets. Furthermore, the digital twin (DT) and machine-learning algorithms will be utilised in this regard so that they can diagnose and anticipate potential defects, not just those that are already visible and present. Moreover, at the advanced level of the industrial automation pyramid, predictive and decision-making strategies can be deployed through a virtual representation of physical assets not only for the automation and control level but also for both maintenance and management levels. According to B. Ralph et al. [40], a six-layer digitalisation architecture was developed and integrated into a fully integrated cyber–physical production system for the rolling aggregate as a new retrofitting approach for the transformation of outdated machine systems into a low-cost, smart, and user-friendly approach with machine-learning algorithms. Digitalisation of sensors and controllers in conjunction with the creation of digital twin structures included not only condition monitoring and project management-related data but also process data, with the ultimate aim of developing multiple low-cost user-centred CPPs as a result of the smartly retrofitted approach. other initiatives were conducted to enhance the influence of deploying digital process approaches integrated with maintenance techniques, such as A. García et al. [41], who validated the interoperable I4.0 tools with a collaborative maintenance approach for condition monitoring by simplifying the commissioning of condition monitoring systems and through non-intrusive retrofitting development with augmented digital strategies and proactive condition-based maintenance environments.

In order to enhance the criteria of safety and maintainability while keeping times and prices within realistic bounds, retrofitting case studies with the digital twin technology method have been proposed by several authors. F. Di Carlo et al. [42] proposed a digital retrofitting framework for the digital transmission process and applied it to a real case study of a two-phase mixing plant. In this study, the strength and weaknesses of the proposed framework were evaluated by validating the digital twin techniques and Deep Learning algorithms to predict and detect future faults and to improve communication, which allowed for the improvement of aspects related to safety and maintainability [19]. In addition, digital retrofitting effectively and efficiently enables a sustainable impact of the digital transformation process among industrial companies [43,44]. As evidence of this, Lima et al. [45], through simulation tools and cloud, postulated an approach to determine the energy consumption in a manufacturing system, whereas Lins and Oliveira [44] demonstrated in their study the improvement of the energy efficiency of a mechanical arm by deploying a Cyber–Physical Production Systems (CPPS) retrofitting method.

2.2.3. From Digital Twin to Digital Triplet

Evolution of Digital Twin Paradigm

The innovation of virtual representation of physical assets for manufacturing activities through the product life cycle that deals with process modelling, time information modelling, and response to control commands as well as the interconnected physical systems have been prominently devised in the research community since 1989, when a virtual manufacturing system and its real-time control in the real world were deployed by the Intelligent CAD framework and time information modelling system and integrated for both product models and factory models and developed by the research team at Osaka University [46,47]. Consecutively, in 2002 at the University of Michigan, the preparation for the establishment of the product lifecycle management (PLM) system was coined the notion of digital mirroring as a mirrored space model (MSM) of existing physical assets [48]. By 2010, The term "digital twin" (DT) was originally intimated and forged in a draught version of NASA's technical roadmap for imitating the physical and mechanical properties of space vehicles. Despite the analogy among the academic definition of digital twins in academic literature, the contemporary framework that conclusively elucidates the constraints of the creation of digital twins for automation systems and manufacturing processes was formulated by ISO (the International Organization for Standardization). To sum up, the clarification of the digital twin framework turns on the ISO 23247 series is annotated as follows: "A digital twin assists with detecting anomalies in manufacturing processes to achieve functional objectives such as real-time control, predictive maintenance, in-process adaptation, Big Data analytics, and machine learning. A digital twin monitors its observable manufacturing element by constantly updating relevant operational and environmental data. The visibility into process and execution enabled by a digital twin enhances manufacturing operation and business cooperation" [49]. In contrast to the previous definition, a digital twin is unique in that it fully integrates the transmission of information between physical and virtual counterparts. Changes made to the virtual system can influence the physical object since they are replicated in the virtual system. Other than being a virtual depiction of physical assets, the bidirectional transfer or allocation of data between the physical assets and the digital counterpart, including quantitative and qualitative data (related to material, manufacturing, process, etc.), historical data, environmental data, and, most notably, automatically bidirectional real-time data, is something that retains most definitions of DT. Obviously, DT depends on the level of integration [50]. It coincides with the concomitant and rational evolution of interfacing forms that are aggregated virtual and real terminals, which were referred to as digital models that do not transmit data automatically between physical and digital objects and digital shadows, that is an improvement to the digital model since it incorporates a one-way communication link between the physical system and its virtual equivalent. In the digital model, the physical model can manually transfer data to the virtual object as a result of a state change, and vice versa. On the other hand, with digital shadow, the data automatically flow from the physical object to the digital counterpart, but this is still manual from the digital assets to their physical counterparts. Figure 1 depicts the major components of digital models, digital shadows, and digital twins, as well as the type of data flow deployed in each. As depicted in Figure 1, the digital model does not retain a direct connection to the real world. One of the most important uses of real-time data communication from the physical world to the digital realm is the creation of a "Digital Shadow", which occurs when a change in the state of physical assets immediately triggers a corresponding change in the digital counterpart of the asset. On the contrary, the digital twin is created through two-way, real-time data transmission between the real world and the virtual one, in which the digital twin retains enabled applications in production planning and control, maintenance, and layout design [35].

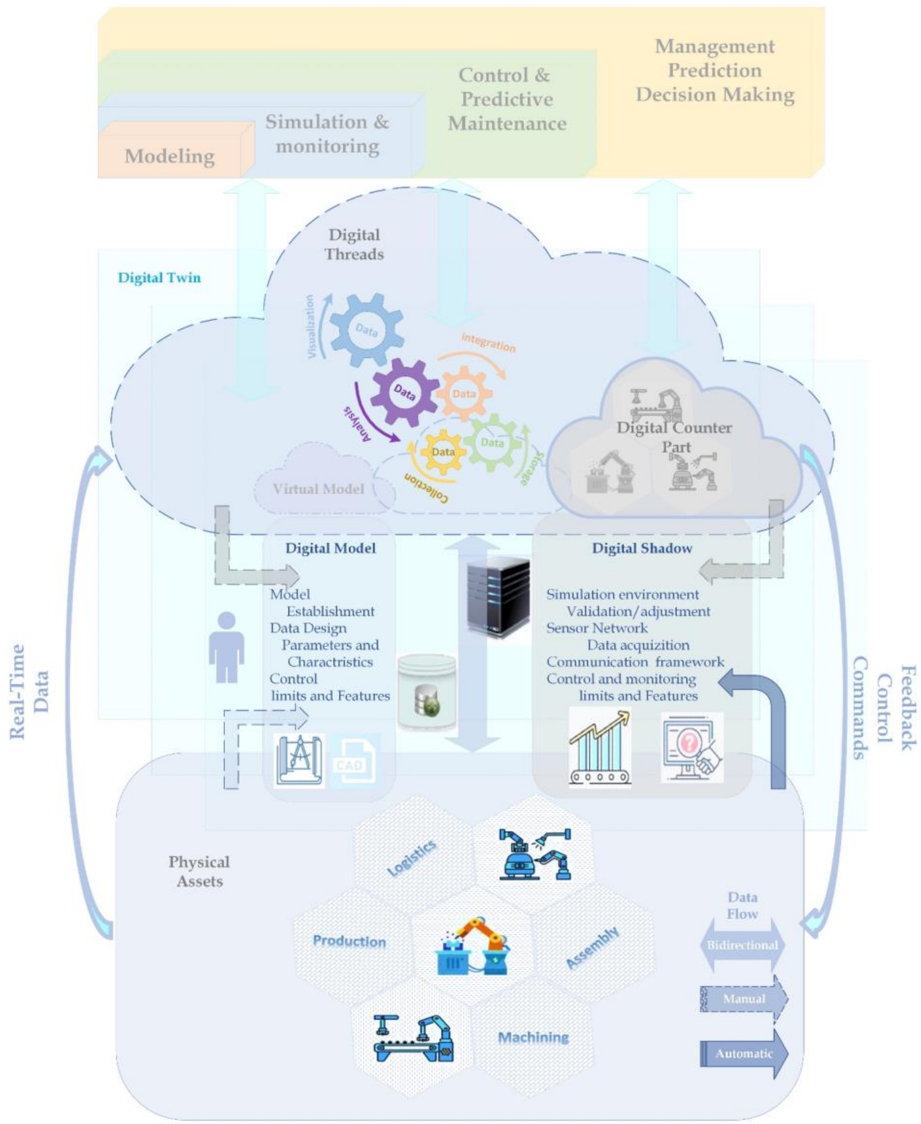

Figure 1. Integration levels of digital twin and data flow through the digital threads deployed in each level.

Digital Thread and Communication Protocol

A digital thread is an integration framework for communication that directs both a real-time and data-driven digital analysis of the information toward the development and optimisation of both physical and digital processes; it enables the holistic analysis and traceability of information propagation and aggregation in order to connect and digitally denote the information generated throughout a product's life cycle [51]. Industry 4.0 emphasises both the horizontal and vertical integration of data, in which manufacturing flexibility, planning, and reconfiguration will be influenced. Therefore, to facilitate the integration of information, the adoption of a communication protocol must be carefully considered. In the literature, multiple communication protocols have been developed, including WebSockets Io, DDSI-RTPS, Modbus, OPC classic, CoAP, and MT Connect [51,52]. Open Platform Communication (OPC) is a communication protocol that allows for the stable and secure flow of data across industrial hardware components. It comprises a set of technical standards that demystify the interface between network nodes and servers. OPC Data Access was the first OPC Classic specification, launched in August 1996, with the initial version in 1997. The standard swiftly gained commercial support, leading to its adoption as an industry norm. However, several hurdles were encountered during the initial adoption stage of the OPC server; these obstacles include problems with firewall protocols on the web, that access and data security were not initially priorities, and that utilisation was strictly prohibited from working with operating systems other than Windows. To overcome these challenges, the technical standards were modified to aggregate the various address spaces and future-proof the protocol, and the interoperability issues across automation software and hardware platforms needed to have their boundaries and constraints removed [53]. However, there is not a simple "either/or" choice between protocols such as OPC UA, HTTP, and others. To varying degrees, certain protocols are more effective in different situations. OPC UA and MQTT are used in current industrial networks because of their usefulness in a variety of applications. Working together, their individual benefits are amplified while any drawbacks are nullified. Existing proprietary middleware is typically coupled with legacy programs and SCADA systems. Therefore, we realise that for basic applications, HTTP/REST is ideal (it is as facile as possible) [53]; Figure 2 defines the decision tree to decide between OCP UA, MQTT, HTTP, and other proprietary IIoTs.

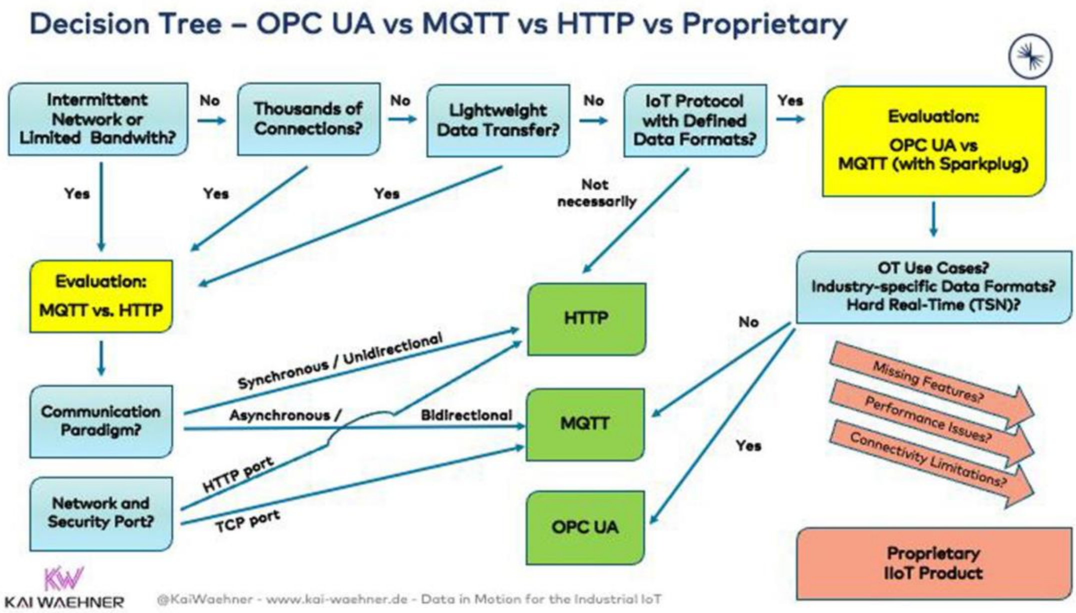

Figure 2. Decision tree to decide between OCP UA, MQTT, HTTP, and other proprietarys IIoTs [53]. Reprinted with permission from ref. [53].

The Hypertext Transfer Protocol (HTTP) is universally supported, widely documented, and easy to implement. There is no requirement for external software, APIs, or middleware. It permits utilising extra standards and supports secure data interfacing among servers and client–server interactions. An Apache HTTP server has the capacity to execute local functions, which are scripts that can be developed to carry out a variety of tasks, including the processing of data. Deploying WebSockets Io as a bidirectional protocol for communication via a web server, which is extensively used by browser-based applications to enable the webserver to transmit information to the client asynchronously. Because of this configuration, it was able to aggregate machine-learning modules into the HTTP server, which facilitated the accomplishment of intelligent world activities by directing the performance of tasks related to analysis and decision-making [53,54].

Despite the fact that optimal modern industrial networks utilise HTTP, OPC UA, and MQTT for real-time messaging, storage, data integration, and data processing through smart factories, Industry 4.0, or Industrial IoT (IIoT), means that massive exchanges of information and data generated for real-time monitoring and control are increasing and must be transmitted, filtered, analysed, and made available through systems in near real-time. To be more specific, the delay should be in the millisecond range. More flexible and adaptable network solutions are required to address the essential issues. From the perspective of a communication network, it is obvious that considerably greater performance is required in terms of communication bandwidth, latency, real-time behaviour, security, stability, and connectivity. This increase in basic requirements can only be fulfilled in part by using modern technologies. As mentioned in the references [55], emerging solutions such as RT-networks and SDN [56], 5G and optical networks, and wireless communication and IIoT [55] were proposed and evaluated to address communication challenges such as bandwidth, reliability, scalability, and mobility, as well as to improve communication characteristics such as throughput, latency, reliability, security, determinism, standardisation, and performance.

Digital Triplet Paradigm

The adoption of manufacturing digitalisation strategies such as Industry 4.0 is increasing smartly. The manufacturing paradigm is shifting significantly as a result of this. Predominantly, engineers have gained an understanding of the physical world by observing it intimately with real items and machine tools, and then by tangibly embodying their ideas in the world through the production process, in which the digital world is substituted for the real one, cutting out the engineers of the process. As a result, engineers are forced to change their approach to interacting with the physical world and its virtual counterparts. This degree of digitalisation entails crucial solutions for a diverse range of problems in futuristic industries and, notably, in typical factories. For endorsing such engineering activities, the paradigm of 'digital triplet' was developed by a research team from Japan at the University of Tokyo [57]. Umeda et al. [57,58] coined the concept of the digital triplet "D3", which integrates an intelligent activity world throughout the cyber and physical worlds and empowers manufacturing system engineers to consolidate and ennoble digitalised engineering processes that encompass the digital and physical worlds. Contingent on this, the digital triplet "D3" paradigm is now being seriously canvassed as an approach to untangle these two significant problems that have been affecting Japan's manufacturing sector [25,57–60].

- The current digitisation trends may not complement the manufacturing industry's style, resulting in the extinction of the manufacturing sector's strengths.
- Engineers and technicians struggle with digitisation. Digitalised manufacturing systems reform planning, design, construction, operation, maintenance, improvement, and replacement. Instead of merely integrating and improving manufacturing processes in the physical world, engineers should also use the digital realm by deploying intelligent activities.

In addition, a rational conviction of the digital system reference for the production environment was depicted by researchers from the Netherlands at the University of Twente as a digital triplet [26] in order to exemplify the role and obligation of the digital twin paradigm for making predictions, adjustments, and influencing decisions by dedicating machine learning to the digital transformation. The three interactive parts of the digital systems were implied with the following depictions: the digital twin is the duplication of the system by the conglomerate of data, information, models, methods, tools, and techniques; the digital prototype is the envisaged state of the emulated system; and the digital master is the anticipated state of the system's validity and adjustment by dedicating (machine) learning in emulated efforts [24,26]. As elucidated in Figure 3, the intelligent activities layer and the master part of the digital system are the advanced levels of the conventional digital twin paradigm. The digital triplet concept was conceived as an implication of intelligent evolution; thus, it urges the merging of the real, virtual, and intelligent activity worlds and human awareness in order to forge futuristic research into the various strategies for embracing this digital transformation's smart and intelligent potential.

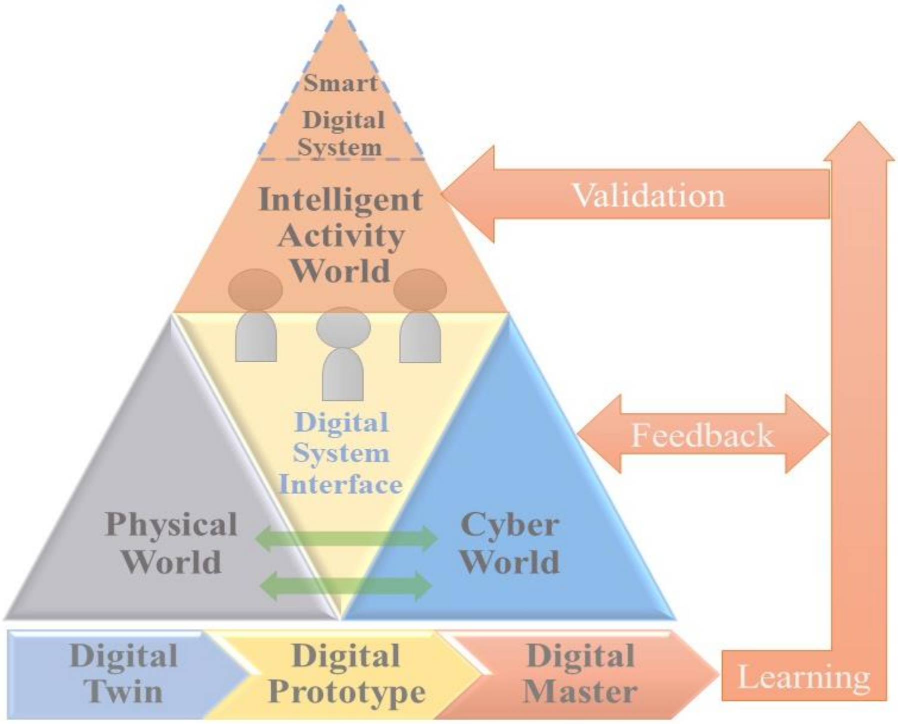

Figure 3. The interaction of the novel paradigms of the digital triplet 'D3' notion.

In order to overcome any uncertainty and ambiguity regarding digital paradigms, namely "digital triplet and associated concepts like digital twin, digital shadow, digital model, and digital thread", a tabular representation is established in Table 1 to define the differences among previous concepts. In this table, the contribution of the physical, cyber, and digital worlds as layers in each digital paradigm [35], the enabled application, the enabling technology, the contribution of the human, and the data transition are defined.

Derived from this analogy, we can define the digital triplet concept as a viable system with a multi-function digital interface that iteratively revives and is virtually deployed with two-dimensional real-time data transfer among the physical, digital, and cyberspace. D3 mileages are obtained by utilising an appropriate digital twin for anticipating scalability, autonomy, innovation and achieving optimisation and predictive analytics. Holistic data aggregation can be realised by leveraging human knowledge and creativity, artificial intelligence, and machine learning.

Table 1. The analogy among digital triplet and associated concepts like digital twin, digital shadow, digital model, and digital thread.

Constituents of the Digital Paradigm	Digital Model	Digital Shadow	Digital Twin	Digital Triplet
Physical Layer	• Technical information • Parameter • Mathematical models	• Technical information • Parameter • Mathematical models • Sensors	• Technical information • Parameter • mathematical models • Sensors, actuators, and controller • Assets, systems, and processes	• Human • Assets • Process • Technology
Digital Layer	• 3D model • Virtual model	• Digital mode • Data storage	• Digital replica (digital model and digital shadow) • Data storage	• Digital Twin
Cyber Layer	-	-	• Cloud processing • Big data storage	• Digital replica with AI to create hyper realistic cyber space
Contributions & Enablers	**Digital Model**	**Digital Shadow**	**Digital Twin**	**Digital Triplet**
Data Transfer	• Offline	• One-way real-time data from the physical layer to digital layer	• bi-directional real-time data communication between physical and digital space	• Two-dimensional real-time data communication over cyberspace
Enabled Application	• Creation • modification • modelling	• Creation • Modification • Modelling • Data acquisition • simulation	• Modelling • Simulation • Modification • Analysis and optimisation • Monitoring and controlling • Diagnostics • Prognostics	• Optimisation • Monitoring • Controlling diagnostics • Prognostics • Predictive maintenance • Decision making
Enablers	• CAD • CAM	• CAD • CAM • SCADA	• IoT • Big data • Cloud technologies	• IoT • Big Data • Cloud technologies • AI and ML • Cyber security • Augmented reality • Virtual reality
Human intervenes In process and decision making	Direct	Direct	Direct	Direct for the human as an avatar for the process and indirect for decision making
Digital Thread	-	-	framework for a real-time, data-driven, and digital analysis	framework for a real-time, data-driven, and digital analysis

As shown in Table 1, we can consider the digital triplet paradigm as a development of digital paradigms at the lower integration level. The constituents will contribute with real attributes of the physical layer, the dedication of digital facilities to create a virtual replica of physical things in different digital file formats combined in the digital world, and the ability to achieve hyper-realistic cyberspace by a powerful, emerging, and interconnected digital paradigm with advanced intelligent features such as big data, IoT, ML, and augmented reality, in which the cyber layer will accomplish several competitive advantages, including data privacy, scalability, prognostic, predictive maintenance, and controlling and independent decision making in comparison with the digital layer. All of these constituents will have their enablers according to the related digital paradigm and will enhance the applications and technologies that will benefit from each paradigm with an integration framework for communication as a digital thread; the influence of digital threads will be initiated starting from developing the digital twin paradigm.

3. Digital Triplet D3 Hierarchy for Digital Retrofitting

To identify the essential areas of the development hierarchy for intelligent digital twins (Figure 4), we postulated four separate levels of the digital triplet. The levels are the result of a rational classification of literature reviews during the last decade [24–33,57–60]. The development hierarchy of the digital triplet D3 as an outcome of intelligent activity based on human knowledge and learning activities is defined by concept map theory, which is an explicit representation of knowledge for enhancing meaningful learning [61,62]. Knowledge transfer can be defined into two types: explicit knowledge, which includes documented instructions for facilitating activities, and tacit knowledge, which pertains to intuitions, experiences, and how it is possessed by active individuals [62]. Derived from the mathematical formulation of the concept map proposed by A.M.M.S. Ullah [61], the constituents of the concept map denoted as CM are as follows: Focus Question (FQ), a set of concepts CP = {CPi | i = 1, 2, . . . }, a set of relationships or propositions RE = {REj | j = 1, 2, . . . } showing the linguistic or mathematical relationships among the members of C, a set of syntactic phrases SP = {SPk | k = 1, 2, . . . } that are needed to create a set of propositions using the members of CP, and a set of documents added to concepts denoted as DC = {DCil | l = 1, 2, . . . , i = 1, 2, . . . } consisting of text, mathematical and logical derivations, videos, sounds, pictures, illustrations, computer programs, and/or the links to other concept maps. Thus, a concept map is given as follows: CM = (FQ, CP, RE, SP, DC) [61]. For the digital triplet hierarchy, the concept map encompasses the following constituents: FQ = "Determine the Digital Triplet", CP = {decision making, prediction, knowledge, experience transfer, intelligent activity, machine learning, artificial Intelligence, dominate, monitoring, metadata, real-time data, data acquisition, imitate, virtual counterpart, digital replica, attribute, parameter, tasks, feature}, RE = {Prediction of the attribute of the system can be conducted based on the experience transfer from the expert engineer to employ machine learning, intelligent activity will train historical knowledge for prediction and decision making, validating and testing the predicted attribute of the system should be conducted with real-time data rather than historical knowledge and metadata, control tasks of the predicted behaviour will be a result of concatenated execution of real-time monitoring and data acquisition, emulation in real-time by acquired data from a set of signals, physical tasks duplicated by virtual counterpart}, SP = {of, can be, by, will be a result, from, based on, . . . }, and the links to other concept maps from the respective concepts DC = {DC21, DC41, DC51, DC61, DC71} = {Digital Twin, ISO 23247, anomalies detection, predictive maintenance, programming, ... }. In order to correspond with the focus question, the relevant contents of the respective digital twin concept of a system and process were combined to culminate in a holistic level of the digital triplet.

As a result, the holistic level of the digital triplet hierarchy can be clarified as follows: the first level is the duplicated level, an a priori representation based on our knowledge of the physical world's automated process. This level consists of a digital model that duplicates a certain attribute of the physical counterpart, as well as characteristics and technical data required for the system's virtual design. At this level, high-fidelity physics models can provide a priori simulation outcome predictions and scrutinise numerous scenarios in automation and machine retrofitting, avoiding the requirement of several trial designs with inaccuracies. However, because it is sedentary, the digital twin does not directly detect process fluctuations and uncertainties in the real world, and its prediction value is confined. Developing by observation and data acquisition, the second iterative digital twin matures and becomes more sophisticated as sensor data are used to build the physical–digital interface, allowing for better predictions and the cultivation of a real-time virtual representation of automated tasks. A virtual version of the physical part paves the way for observing and predicting the behaviour of operating tasks and system performance before it is performed. This has the capacity to be deployed in real-time monitoring of the physical components by utilising the virtual part's attributes, and it has been envisioned as part of a digital part validation process. To optimise the validation process of the acquired data, the concatenated level avails control and domination of the automated process in real-time. By utilising either feed-forward or feed-back control, a control system can set up a bridge that can interface in both directions between the virtual and real worlds. A virtual version is observed through the utilisation of sensor data and quick model predictions and the dominated digital twin fulfils the specifications of a real-time monitoring and control system and physically updates the control command. The perceptive level is the culmination of this process; it is the paradigm of digital triplet D3 that assimilates so much awareness of human knowledge for decision-making and predictive maintenance based on artificial intelligence (AI). In situations in which the breadth of data from sensors, model predictions, and process parameters impose limitations for simple control systems, the intelligent activity layer with AI systems enables holistic data aggregation and appropriate control inputs to the physical system. In more specific words, it can serve as an autonomous system to adjust control parameters, as well as detect anomalies and eliminate or correct errors as they postdate or coincide with intelligent prediction. Our proposed framework depicts how digital systems might evolve to take more control over the AI and provide helpful semantics for identifying digital triplet D3. The proposed levels are concluded in Figure 4 as follows:

- Volition: the perceptive level, which exploits human experience and creativity through the application of machine learning to eliminate the need for direct intervention in complex decision-making and analysis features for fully autonomous validation and optimisation of the process.
- Domination: the concatenated level that adjusts and controls the physical system utilising the system's predictions of its virtual representation and sensor inputs.
- Maturity: the iterative level refers to the instantaneous observation of the actual behaviour of the physical system using the sensors, which will then be used for the purpose of system emulation in real-time data.
- Sedentary: the duplicating level with physical task awareness that visualises and emulates virtual features of physical counterparts

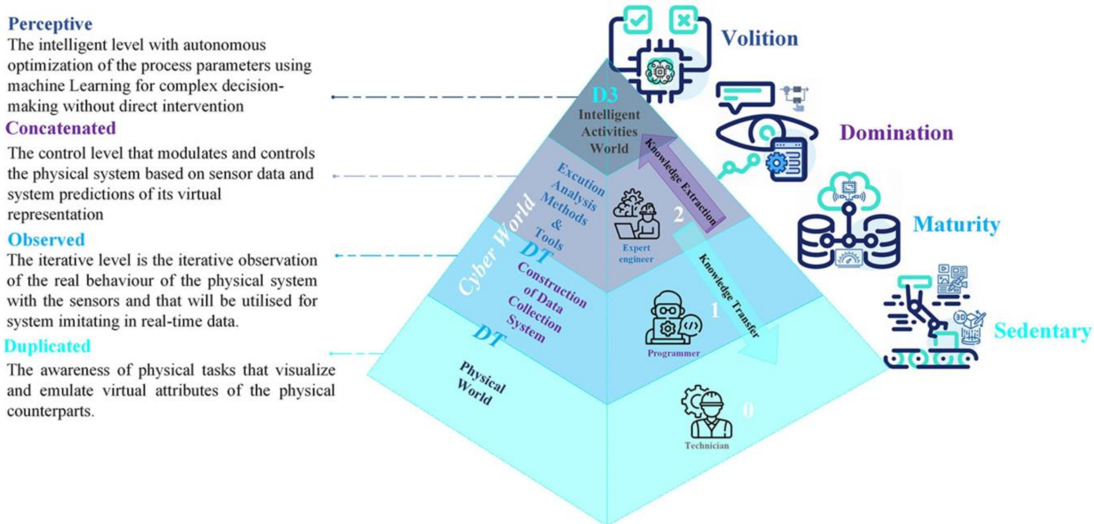

Figure 4. The integration levels of the digital triplet 'D3' hierarchy.

4. Design of the Digital Triplet Paradigm for Retrofitting of Drilling Machine

4.1. The Aggregation of Intelligent Activities with Digital Twin and Digital Threads

In general, artificial intelligence (AI) and machine-learning (ML) technologies are being employed to execute a broad range of Industry 4.0 operations, including predictive maintenance, health monitoring, fault diagnosis, adaptive control, and operational process optimisation. As demonstrated by several studies, the integration of such initiatives into digital twin technology has been evaluated in a variety of industrial situations. The aggregation of AI and machine learning with digital twin technology promotes the interaction between virtual and physical things, enhancing processes and operations to be analysed, predicted, and optimised. The possibility of achieving an intelligent digital twin 'digital triplet D3' paradigm is attainable because digital twin technology not only cultivates the usefulness of virtual simulation, but also enables the interaction and execution of intelligent activities across physical and virtual domains throughout a system's operation. Artificial intelligence and machine learning require consistent access to data sources in order to derive information from systems. The Node.js open-source environment and Apache HTTP Server, which provides a platform-independent interoperability standard for transmitting data between operating systems and devices, can help tackle this need. Intelligent services may only use data to optimise operations or perform predictive maintenance if the appropriate connectivity levels and standards are satisfied. Regarding the mathematical formulation described in the references [61], semantic modelling as a human comprehension of implementing human knowledge with intelligent activity is utilised to explain the anomalies detection procedures among the digital triplet paradigm as follows: let V and C be a vibration generated through the operation of the drilling machine and a set of conditions that will determine the anomalies, respectively. Let E(V,C) be the set of expected states of vibration generated for C. Let M(V,C) be a model (theoretical model for the vibration) of V for C. Thus, using M(V,C), the expected states of the vibration can be determined whenever needed, that is, M(V,C) $\rightarrow$ E (V,C). In reality, both M(V,C) and E(V,C) may not be known beforehand due to the lack of knowledge or any other reasons. Consequently, for the experiment conducted through the drilling process, we will consider that a set of the tested features of the vibration for the proposed condition are Tx(V,C) with reasonable precision and accuracy. A model defined as Mx(V,C) can be reverse-engineered using Tx(V,C), that is, Tx(V,C) $\vdash$ Mx(V,C). For the vibration signals acquired for the anomalies detection process and real-time monitoring, we proposed the following annotate: we will consider Sl(V,C) as samples of (V) vibration signals acquired by the Arduino Nano 33 IoT accelerometer for (C) the normal and anomalies signals during the operation cycle as an experimental data sets, the trained neural network a classification and prediction model of the vibration signals for the proposed condition in normal operation and in anomalies status can be defined as MLP; therefore, using SL(V,C) for training and testing, the trained model is, Sl(V,C) $\vdash$ MLP(V,C). Considering that Sv(V,C) is the sample of the vibration signals used for validating the MLP model, the MLPs(V,C) $\rightarrow$ Sv(V,C) will be used for validating the data sets, for real-time monitoring the real-time vibration signals denoted as Sr can be classified using the proposed model if the {Sv(V,C) and Sr(V,C)} are close to each other with reasonable precision and accuracy. Therefore "Sl(V,C) $\vdash$ MLP(V,C)" is a machine-learning model for anomaly detection through classification and prediction that can be a response to a concept map regarding intelligent activity deployed in the digital triplet paradigm, which is depicted in Figure 5.

The proposed MLP neural networks represent a choice in logic as an approach to detecting anomalies. MLP is a feedforward ANN that consists of one or more parallel layers of nodes placed between the input and output. As for the ANN's structure, the representation of the structure and the example of vibration signals used for anomaly prediction and classification in this paper is shown in Figure 6.

The use of sigmoidal and logarithmic functions is common in nascent strata. Activation functions are frequently used in lower strata while linear functions are used higher up. The "backpropagation" learning algorithm is used in MLP neural networks. All tests contained in the database are firstly processed and secondly, three different datasets are created: a training dataset, test dataset, and validation dataset. Part of these datasets is used for the training phase and the testing phase, while data are kept aside for validation of the final model. The procedure used for the intelligent activities by deploying the MLP neural networks in this paper is shown in Figure 7; the flowchart of the used procedure depicted in Figure 7 represents the ML tasks performed in this paper starting from data acquisition and data processing until anomaly prediction by real-time signals and the anomaly detection task.

To improve the performance of the final model, the datasets were balanced by increasing the data on the training and test dataset against decreasing the validation dataset. The final datasets consisted of different test lengths, thus obtaining different durations depending on the tests performed. The three datasets also consisted of 10 different speeds (800 to 2400 rpm) of the drill press to have a larger amount of data to classify. As for the dataset containing the training and test data, this was split into two: 70% was used for training and the remaining 30% for testing. Training was carried out with a series of iterations that changed the parameters of the neural network, and different values of classification accuracy were occasionally obtained. These accuracy values were compared between training and testing to check how well the model could classify the dataset each time. The classification performance was proved by the result of the accuracy and precision among model training, testing, and validation with the proposed conditions. Table 2 depicts the classification results.

Table 2. MLP classification results.

	Training	**Testing**	**Validation**	**Validation Precision**
STD. COND. (s)	270	270	30	100%
AN. 1 (s)	270	270	30	87%
AN. 2 (s)	180	180	120	100
Accuracy	100%	95.83%	95.77%	

4.2. Design of the Digital Triplet Paradigm for Retrofitting

This research contrived to outfit a retrofitting approach with holistic monitoring that may be used for most, if not all, conventional drilling machines depicted by the process diagram in Figure 8. It proceeded by developing a virtual replica of a model drilling machine that was interfaced with its physical counterpart and imparted vital information in real-time interaction.

Communication and data exchange between the web server and clients were accomplished by employing the advanced features of the Node.Js open-source server environment. The Arduino Mega and Node Js open-source platforms were employed to create an intelligent cyber model of the affordable intelligent retrofitting paradigm. Following the design, the physical system was built and programmed to perform standard machining functions. The socket IO real-time, bi-directional communication protocol was then deployed to establish interaction between the virtual and physical models. Authentication was accomplished with a camera and an Android App to augment the cyber security capabilities within the system's cyber counterpart, in addition to standard control, automation, and real-time monitoring. Furthermore, the anomaly detection and vibration analysis modules were integrated into the server to evaluate IoT data from the vibration sensor, sensor data for safety, and image information transmitted from a camera. Anomalies were detected using this module, and action was taken to estimate the defect consequences and select the decision for predictive maintenance strategy. The contribution of the camera-based cyber security system and machine-learning module improves the performance of the digital twin, upgrading it into a digital triplet. To transfer and convert the data generated by the traditional drilling machine's operating behaviour, a retrofitting paradigm based on the digital triplet hierarchy was used, with digital twins that follow the principle of utilising digital twins in industrial automation and integrated intelligent activities based on human awareness, in which the retrofitting procedures were fulfilled to emulate a digital replica of a traditional drilling machine as a physical asset.

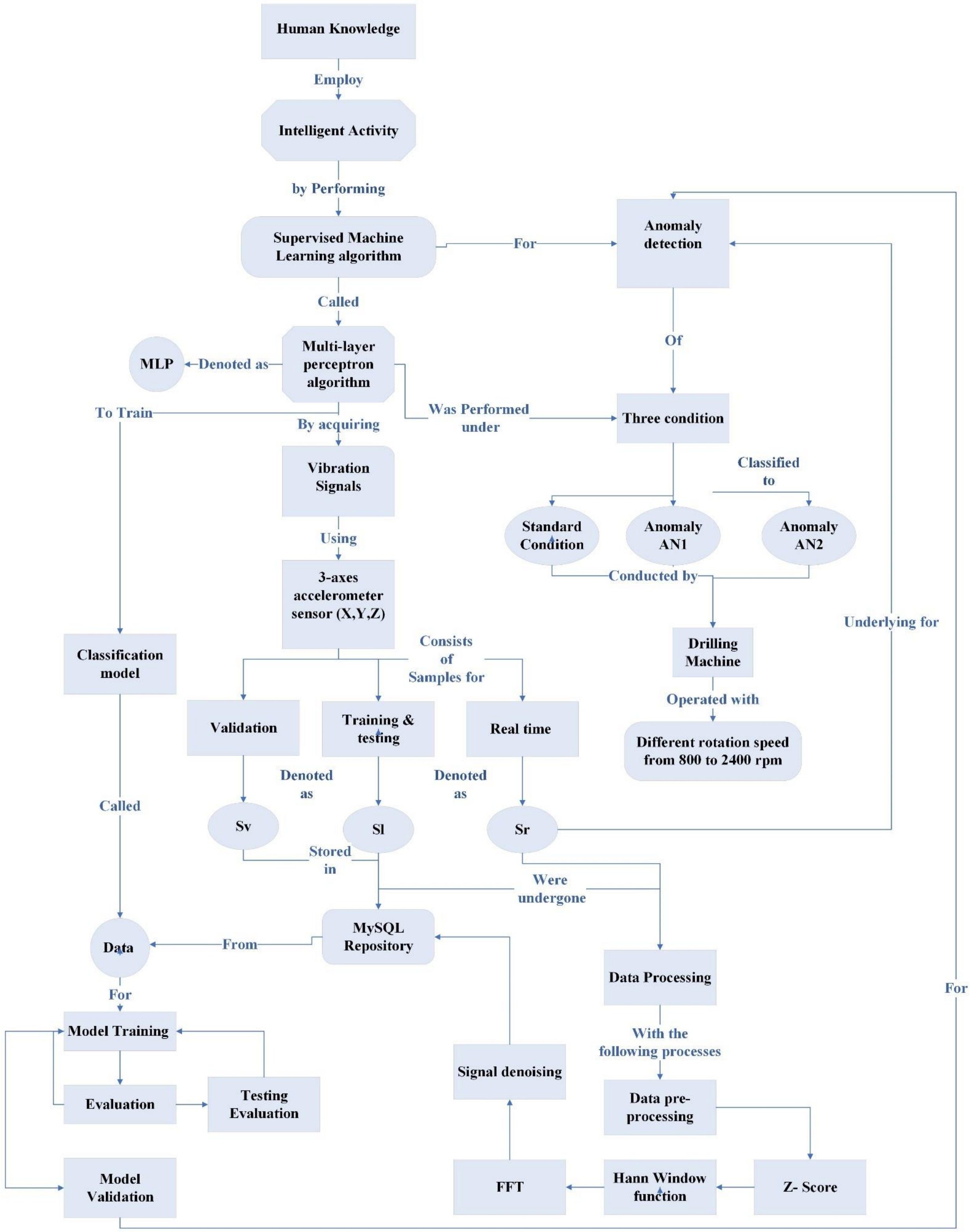

Figure 5. The concept map of intelligent activity deployed in the digital triplet paradigm.

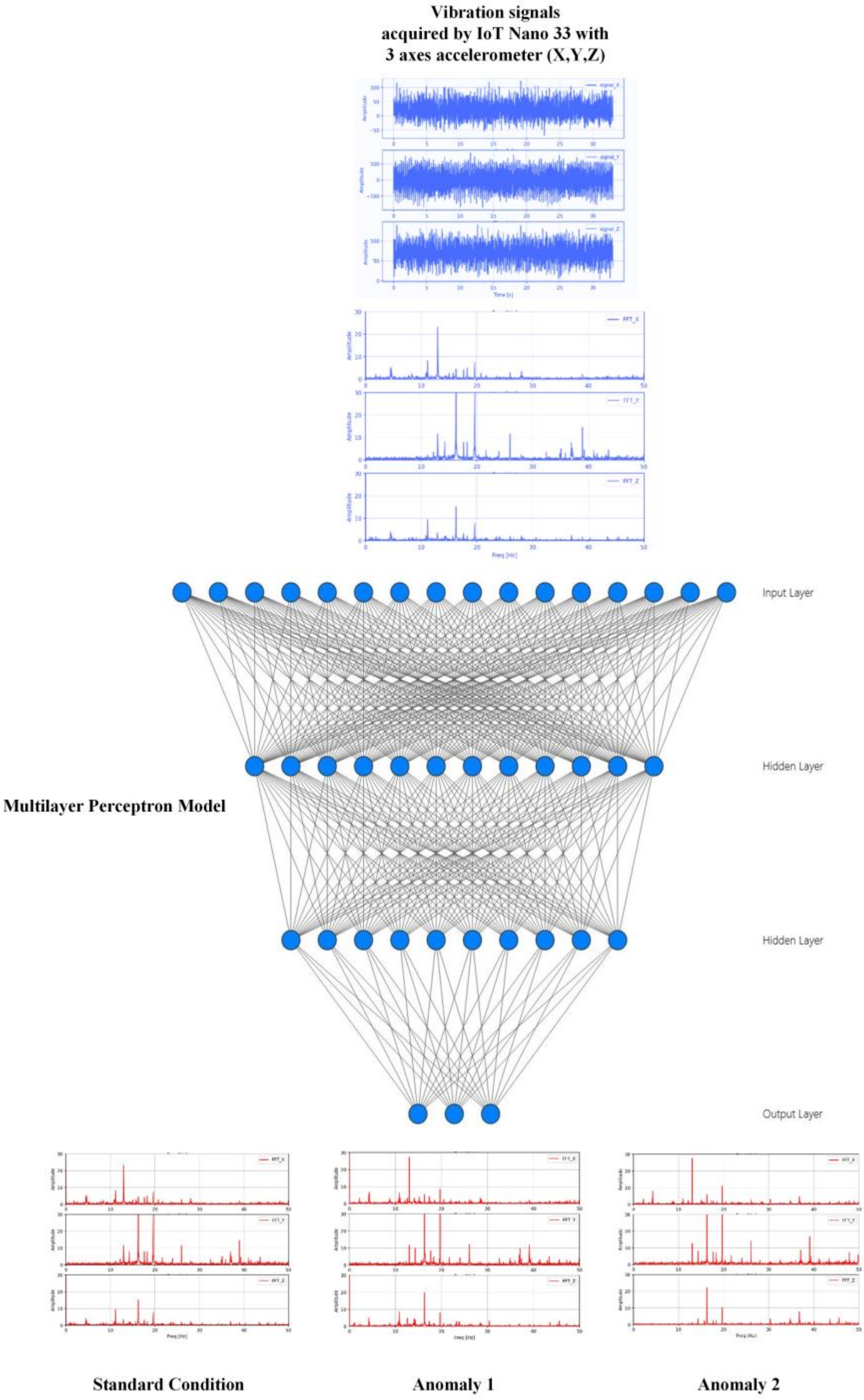

Figure 6. Multilayer perceptron model: MLP ANN structure for anomaly detection with vibration signals.

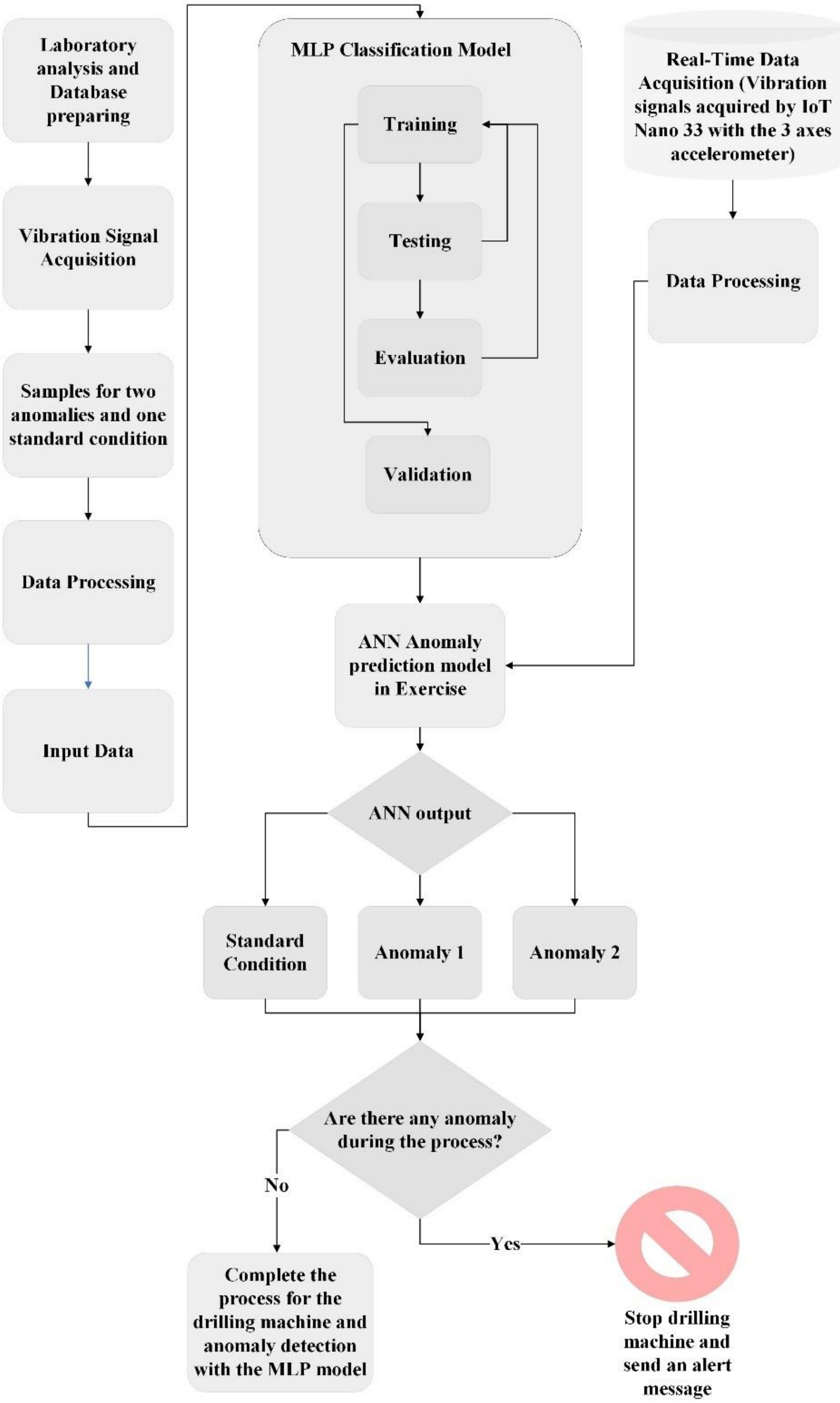

Figure 7. Flowchart of the used procedure in ML tasks, data acquisition, data processing anomaly prediction by real-time vibration signals, and anomaly detection task.

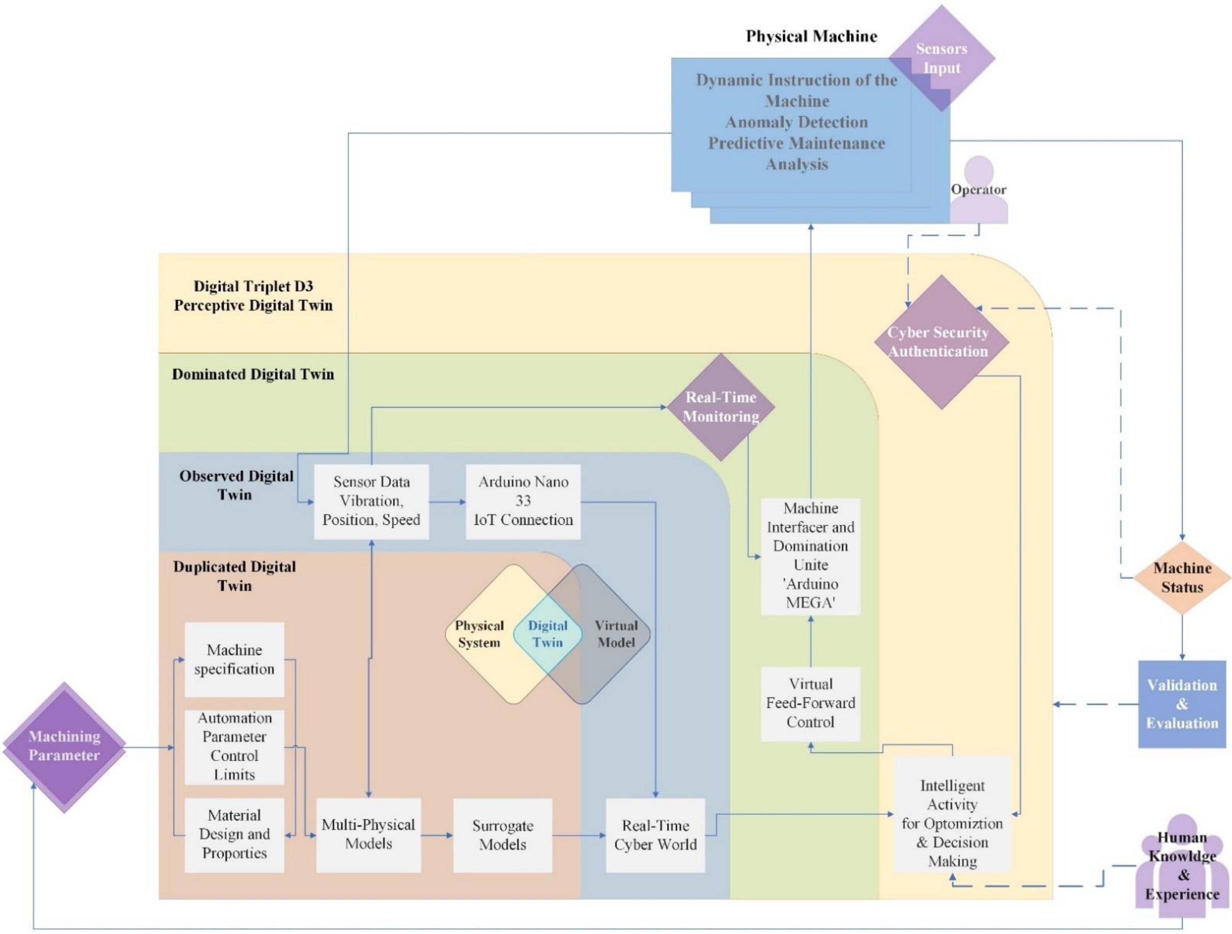

Figure 8. Process diagram and interactions of the key components of the full hierarchy of the digital triplet system for the digital retrofitting paradigm.

The adoption of a digital triplet for digital retrofitting of conventional machines entails emulating a physical system in cyberspace using a virtual model for simulation, monitoring, and control, as well as the use of artificial intelligence to improve system functionality. Figure 9 depicts the configuration and interface layout utilised during project implementation. The system's primary components are as follows:

- Physical Asset:
    - Universal Drilling Machine.
- Controller and data transmitted interfaces:
    - An inverter 'Schneider electric Altivar machine ATV320' to adjust the proposed operating condition for torque and the rotating speed. Arduino Mega with ethernet shield for control and data transmission with ethernet protocol.
- IoT and vibration acquisition system:
    - To enhance the proposed retrofitting paradigm with the principle of the fourth industrial revolution, a vibration sensor with Arduino nano 33 IoT and wireless transmission protocol was installed in this machine.
- Communication server:
    - The server node-based JavaScript conducted real-time data transmission among the digital entities and physical assets as a web access platform. For data transmission and repository of digital information generated by the camera and the IoT sub-system, MySQL was used for these purposes.

- Virtual model and real-time monitoring:
    - Hikvision "DS-2CD2045FWD-I 4 MP" fixed mini bullet network camera with a direct stream for real-time generating a virtual replica of the drilling system. The operating condition and anomaly detection based on vibration analyses were remotely detected and iteratively monitored.
- APP Android for Cybersecurity features:
    - Authentication with securely identifying people and digital entities of the physical asset was deployed in this paradigm based on scanning the barcode generated for this machine. In addition, authorisation as a role in defining and implementing privileges for accessing the authentication portal was conducted with a face-recognition algorithm.
- Intelligent activities:
    - AI-Based decision making and anomaly analyses were deployed for vibration detection and classification during operation conditions and safety features.

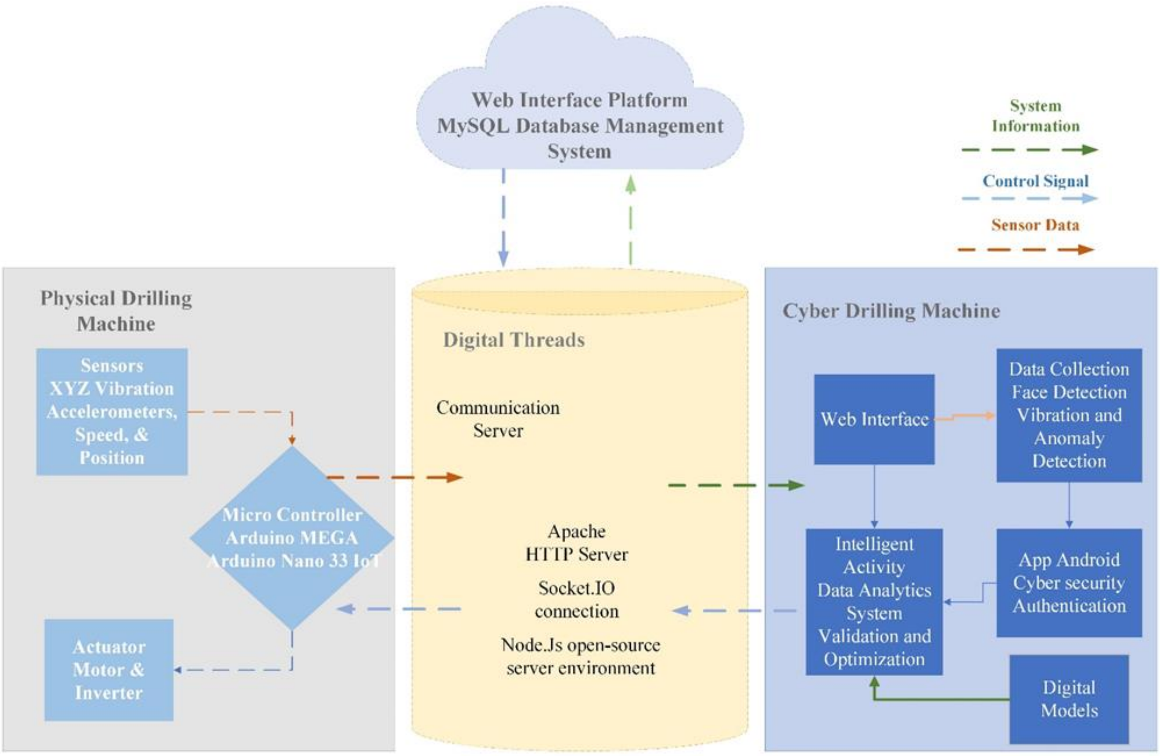

Figure 9. Block diagram of digital triplet system depicting the interface layout with the flow of the data from the physical drilling machine, through the digital threads, into the cyber models of the machine.

5. Result and Discussion

5.1. The Physical Model

To embark upon the first level of the D3 hierarchy, the initial phase 'level 1' for emulating the physical model of the research setup was adopted to be a typical drilling machine; a photograph of this retrofitted physical counterpart can be seen in Figure 10. The physical model was retrofitted with five types of sensors for input signals in order to consider the observation level of the paradigm 'level 2', and the acquired data were the following: the status of the pullies' and belts' guard, as well as the chuck as a safety guard, were evaluated by limit switches, the 60 mm feeding vertical distance of the spindle was measured by a linear potentiometer, the vertical adjustment of the working table was ascertained by an ultrasonic distance sensor, and the vibration through three axes was detected by the LSM6DS3 3D digital linear accelerometer sensor. The capability of concatenated phases 'level 3' between the sedentary level and the observed level was fulfilled with the involvement of the inverter 'Schneider Electric Altivar machine ATV320' in control and modification of the machine parameters, which was evaluated in terms of spindle speed and torque performance, and the open-source Arduino Mega 2560 integrated with an 8-bit microcontroller as the main controller for this paradigm to accomplish communication with Arduino Nano 33 for IoT capabilities, ADC analogue-to-digital converter, and aggregating the digital thread interface. The maturity of the paradigm was accomplished with the MODBUS protocol that allows the Arduino MEGA board to directly communicate with the inverter and decode data from the sensors. Direct connections were amalgamated with the Arduino MEGA; the safety guard for the chuck, the linear potentiometer for feeding the vertical distance of the spindle, the ultrasonic distance sensor for the vertical position of the table, the push-button switch, the emergency stop switch, and the data for the belt box guard was transmitted via the inverter to Arduino.

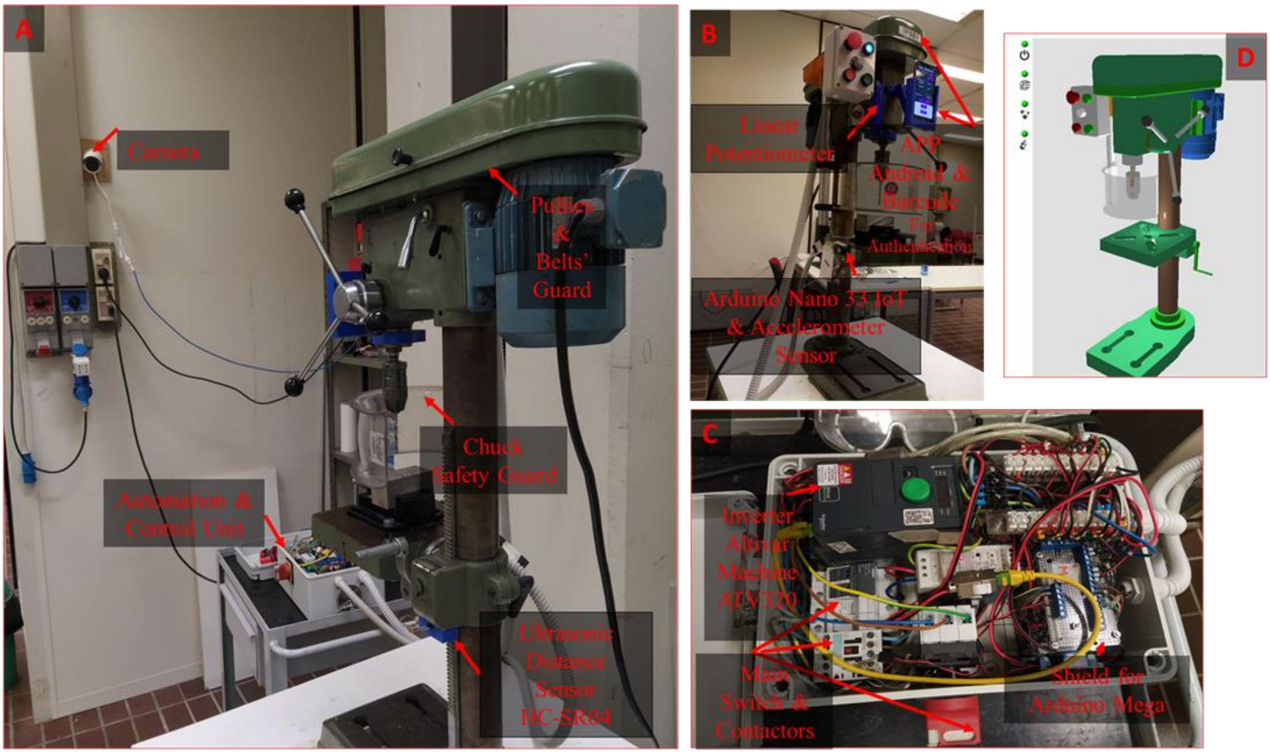

Figure 10. Research setup of the retrofitted physical counterpart and its virtual replica: (**A**) physical assets, (**B**) physical model, (**C**) automation and control unit, (**D**) virtual model.

5.2. The Cyber Model

The two constituents, real-time monitoring with anomaly detection and the digital replica of the physical counterpart, constituted the digital counterpart of the retrofitted paradigm. The cyber-world 'level 2' comprised an evolved status that aggregates the surrogate model of the digital replica of the physical world and the holistic analysis and traceability of information propagation and aggregation among the configuration of the duplication, iterative observation, and initially tertiary integration 'level 3' of the digital triplet D3 paradigm. A friendly human–machine interface for real-time monitoring and the database of the machining parameters were embedded utilising the extension .js "JavaScript", embracing the selection of workpiece material and drilling tool geometry, the generated torque, and the rotation speed of the motor. The proposed digital twin 'level 2' and 'level 3' comprised the three-dimensional model of the drilling machine, which was designed by the 'three.js' JavaScript 3D library, and the acquired information in the process and the virtual replica of the machine were iteratively depicted in the real-time web interface. The deployed web interface platform, which is illustrated in Figure 11, permits the user to monitor the machine with the following parameters: the status indicators and virtual 'start/stop' switch that permit access to virtually operate the physical counterpart, virtual model infallibly imitates the real-time behaviour of the machine, the real-time monitoring based on the camera, the validation of the torque and rotation speed, the machining parameter with the data for the rotation speed, vertical feed in mm, and the displacement of the working table in mm.

5.3. Web Interface Platform and Authentication

The web platform in level 3 interfaced with the local metadata in level 2 and the database in level 4. The log-in interface was devised with JavaScript and PHP scripting languages to enable secure remote monitoring and anomaly detection. The web interface was configured as a client; it could read data variables straight from the node.js server and update the operator dashboards. This proceeded with the digital threads as an obfuscated layer to aggregate the communication between level 3 and level 2, in which the decoded analogue and digital signals through the web socket communication protocol were detected by the web platform from Arduino. The bidirectional transmission of the data was enhanced by the interaction of bidirectional full-duplex communication over a TCP/IP port. Specifically, Socket Io allowed clients such as "Web platform, MySQL—engine MariaDB data repository system, Arduino, Camera, Android App, IoT sensor, and Intelligent activity for anomaly detection and cyber security" to interface with the Node.js. server.

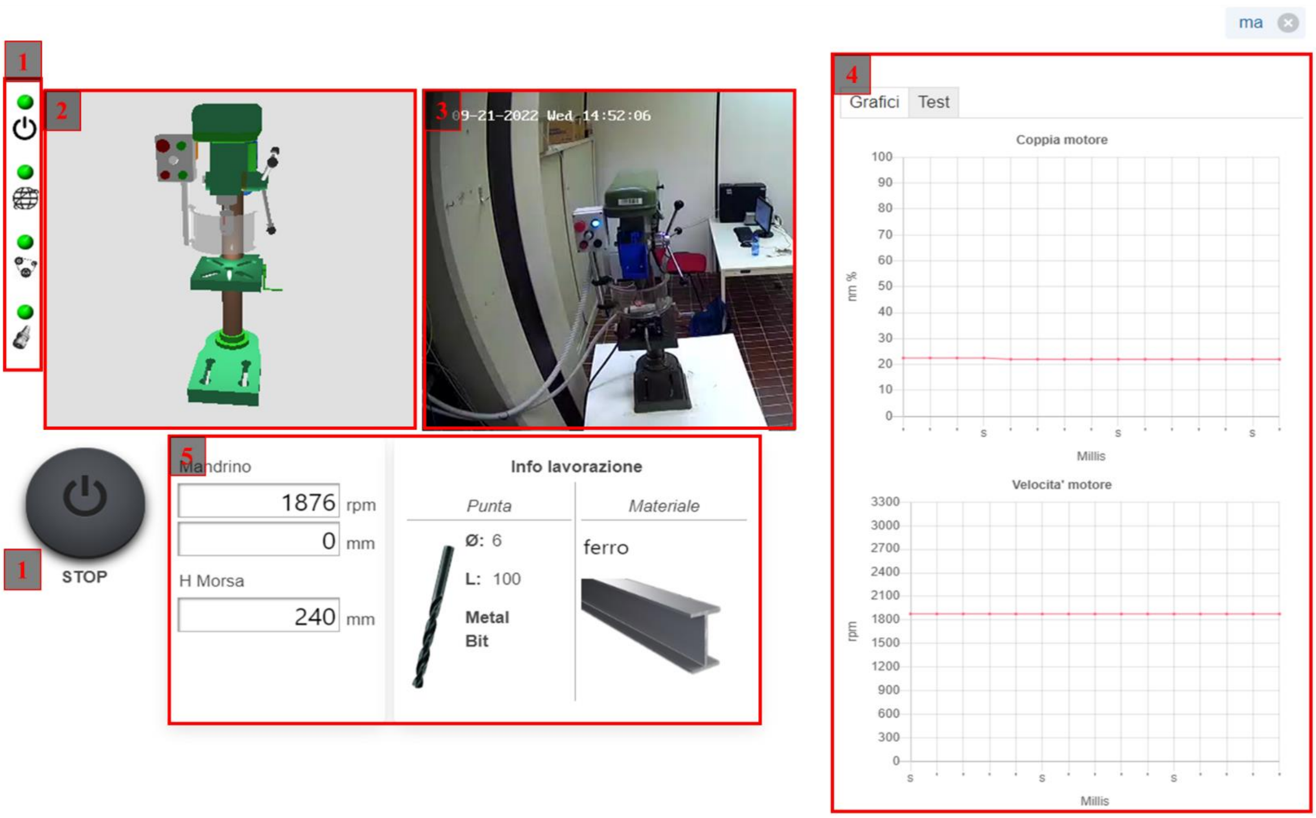

Figure 11. The web interface platform. 1. The status indicators, 2. virtual model, 3. real-time monitoring, 4. the validation of the torque and rotation speed, 5. machining parameter.

Metadata, real-time data, and persistent data were transmitted from clients to servers via the Socket Io, which served as a stream between the NodeJS server, the MySQL—MariaDB, and the Android App on level 4. This was accomplished through the Python Socket IO libraries that permitted several relevant features for bidirectional interfacing with transmitted data. In this scenario, the MySQL—engine MariaDB database management system, a fork of the MySQL database management system, was utilised for the exhaustive deployment of the data repository system at level 4.

To ensure secure access control to unauthorised users for logging on to level 4 of the digital triplet paradigm, the login features for both the cyber word of the machine and the Android App were adopted to increase the cybersecurity function and secure interface design. Adopting the Industry 4.0 initiative is complicated by impediments regarding cyber security. As a result, safeguarding systems against downtimes and attacks requires that IT security and privacy be enhanced at the early design stage of the cyber–physical system. The connection between the web interface and the database server and the node Js server was deployed by a connection string comprised mainly of sensitive information such as the password and the username. Utilising the PHP cryptography extensions, this connection string was encrypted by an existing cryptographic algorithm. A password-based key derivation function was implemented by the $algo parameter and specifying the hush algorithm "PASSWORD_ARGON2I: $hash = password_hash($password, PASSWORD_ARGON2I)". This permitted secure login and authentication for the authorised user. A random string, called a salt, was generated by using a cryptographically secure length of random salt 'salt_len (int)' and was encoded by the 'encoding (str)' Argon2 library for each password to combat unauthorised intrusion into the cyber counterpart of the system. When a user logged in, their username and password were encrypted before being saved in the cloud server's database; when a person logs in, their salt and hash are retrieved from the database and used to verify the password. To verify the user's identity, the database's hash is compared to the given password's hash. The user will access the web interface controls if authentication is successful.

However, although the user had an authenticated login to the cyber world, comprehensive access to all levels of the paradigm is only achieved by secure authentication utilising the Android App. Access to levels 3 and 2 was permitted only by deploying authentication for both the physical counterparts, "machine and cutting tool", by the machine-readable representation barcode and the facial recognition of the human factor "operator". Access to the Android App was conducted in two steps. First was the face recognition or verification of the operator, which is the method of identifying the identity of an individual using their face. The face embedding was utilised in a real-time face detection algorithm built into the Android App to detect where the faces are and adjust the focus accordingly. The Python-based face-recognition library was imported to perform the task of face detection in the video stream, and after that, the face was cropped out of the image in order to embed the face as a vector for machine-learning extraction functions, and the final step for detection was the recognition of vectors 'embedded faces' by comparing the embedding face with the rest of the embeddings that were trained in the previous task. After the authentication was fulfilled by the face of the operator, the next step to access not only the App but also the level 2 'privilege to operate the machine' and level 3 'real-time monitoring and anomaly detection through the operation tasks' of the paradigm was accomplished by scanning the barcode of the machine.

Utilising code 128 for authorised login to the cyber counterpart of the machine, the Java-based Android.gms.vision.barcode.Barcode detector library was deployed for real-time streaming of the barcode scanning mechanism with the camera. Consequently, this demonstrated that the digital triplet paradigm can fulfil not only safeguard authentication to all layers of the digital twin but also immune utilising and monitoring the physical twin in real-time. The authentication steps consist of the following steps as follows: authentication login to the web interface platform, the main home screen of the Android App, authentication-based operator face detection, verification of the operator's face, authentication-based barcode scanning of the machine, and safeguarding authentication to the main activity screen of the App; the machine's barcode and cutting tool barcode are depicted in Figure 12.

5.4. Real-Time Monitoring and Anomaly Detection

Physical counterparts can be observed, monitored, and supervised in real-time via cyber (as in, online) monitoring. In levels 2 and 3, the observation tasks were accomplished by fulfilling this function by utilising sensor feedback from the physical assets. The perspective digital twin in level 4 measured the distance for the feeding vertical distance and then compared it with the critical depth proposed by the operator and acquired by the database of the online cloud data from the MySQL server. In addition to this distance, the vertical height of the working table was ascertained and depicted in the cyber interface by the information configured through levels 2 and 3. The dominating digital twin in level 3 derived the real-time data from the observed digital twin in level 2, depicted the value for each distance in the interface, and implied the decision in level 4 for the status of the drilling machine by demonstrating the online status of the machine with the Android App and web interface.

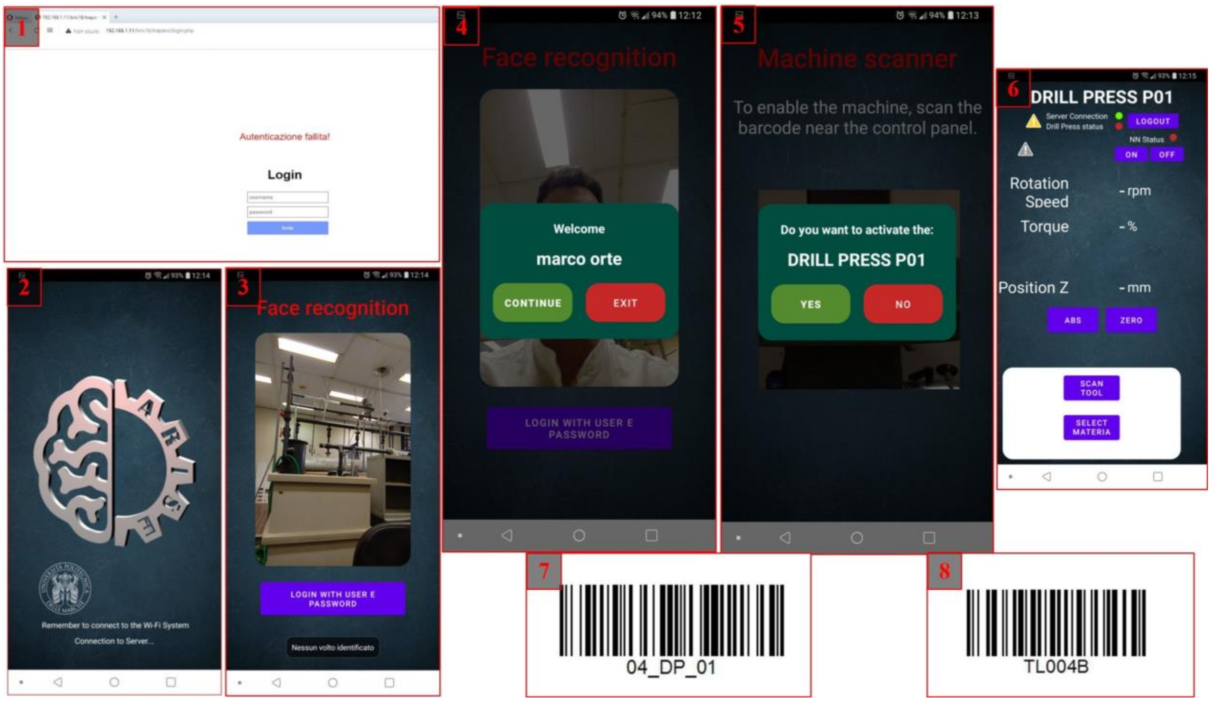

Figure 12. Authentication login to the cyber world of the digital triplet D3 paradigm. 1. Login authentication, 2. Android App, 3. and 4. face detection, 5. barcode scanning of the machine, 6. the main activity screen of the App, 7. and 8. the machine's and cutting tool's barcodes.

For the time interval of data transmission, notable lag and latency will result in real-time monitoring and will impact the digital twin's ability in all levels. In level 2, Arduino mega signaled the external clock that the full packet of all data acquired by the sensors was received in about 50 ms. To ensure that all data and at least two synchronous signals were retrieved, the setup time interval needed to be transmitted per data packet was selected as 200 ms. The minimal response latency was selected by testing sensors and the recommended setup time interval by previous research [63–68], in which the optimal setup time for transmitting data per interval begins at 100 ms, as microcontrollers have a higher throughput data success rate when setup data are limited. This time will eliminate data traffic and will decrease the microcontroller latency with greater time interval setup data [63,67,68]. Furthermore, continuous and thorough vibration signals were transmitted by IoT acceleration sensors. Accelerometer data were retrieved in parallel every 1000 ms and included 100 related previous samples (one every 10 ms). However, due to the transmission latency, data from a sensor node will experience the latency of both the IoT and the cloud. Therefore, the effect of network latency on the setup time interval was reduced by employing a store-and-forward approach [64–66] where the local latency was lower between the sensor node and the IoT. In addition, the data were locally stored in the sensor node with a timestamp and subsequently sent to the cloud by MySQL.

In addition, the anomaly detection for the safety parameters (the pullies' and belts' guards, as well as the chuck safety guard "open or close status") was monitored by the perspective digital twin level 4, recorded, and stored in the repository of the online information and indicated in both the web interface and the Android App with transmitted information by the operation cycle. When an anomaly was ascertained, the fault was detected, and level 4 had the dominant decision for combating the attempt to operate the machine. Consecutively, throughout each cycle of operation, the data that were transmitted by the vibration IoT sensor in level 2 were retrieved, and the pertinent vibration information was then stored in the repository of the online MySQL server, and eventual failures and anomalies were anticipated by the configured historical record of each cycle and the deployed machine-learning algorithm. The vibration failure and the anomaly of the three normal conditions (the fixed vice clamp, spindle clamp, and table clamp) were induced by the incongruous vibration acquired in level 3. Throughout each cycle of operation, the deployed perceptive digital twin in level 4 was configured by the python-based open-source machine-learning library Scikit-learn. The non-linear function for predicting the fault with the incongruous vibration was learnt by training a neural network model on the online vibration data stored in the repository and implementing a supervised learning algorithm with a multi-layer perceptron (MLP) algorithm for classification of the vibration data observed by the digital twin at level 2 throughout each cycle of operation. The accuracy of prediction in vibration status was influenced by detecting the errors from neural network nodes of the anticipated vibration data to input trained data by mathematical backwards propagation of these errors. Based on the information observed in level 3 with the App, the decision to switch off the drill follows neural network anomalies; when this system was activated and an anomaly was detected in the first 3 s of operation, the drill switched off automatically. Thereafter, the digital twin at level 4 detected the last status of the physical twin to diagnose the fault and anomalies that occurred and autonomously accomplished the decision to switch off the machine. Even though the digital twin had the decision to autonomously switch off the machine, the decision for an emergency stop can be fulfilled by the operator on a low-level controller on the observed digital twin at level 2. Respectively, the virtual start/stop switch deployed in the control interface with the web interface platform and then the operation of the physical twin was momentarily eliminated. This diagnosis proves that the digital triplet paradigm could investigate simulated anomalies by observing the state of the physical twin and using sensor feedback from the physical twin. Even though the drive of anomaly detection is confined to the machine's vibration and safety status, the digital triplet paradigm proves to be a viable approach for real-time monitoring and diagnosis. The perceptive digital twin would be able to make intelligent decisions based on the immediate status of the physical twin due to the contributions of levels 3 and 4. An example of real-time monitoring and anomaly detection is depicted in Figure 13. As illustrated in Figure 13 from (1 to 6) 1 and 2. anomaly detection, 3. operating status, 4. indicator of authentication, 5. safety indicator, 6. IoT sensor and feeding sensor indicator, the cyber world imitates and diagnoses physical counterparts in real-time and utilises anomaly detection for the safety parameters (the pullies' and belts' guards, as well as the chuck safety guard "open or close status"). The operating status of the drilling machine was converted from green to red based on the fault in the safety parameters. In addition, from (7 to 10) 7. status indicators and App indicators, 8. the machining parameter, 9. anomaly detection message, and 10. neural network status indicator, the real-time anomaly detection via the Android App was also illustrated with the anomaly detection message 'table not fixed' and the neural network status indicator.

5.5. Augmentation of the Four Levels of Digital Triplet

The potency of the four-level hierarchy's digital triplet was appraised for retrofitting a conventional drilling machine. The appraisal demonstrated the viability of the hierarchy in imitating the real-time functionality of the physical system in cyberspace, an immaculate performance of this paradigm. Hierarchy's usefulness as a digital triplet notion for digitisation and digital retrofitting was dedicated to disclosing intelligent activities based on human awareness and instigating the industries' resilience and flourishing by facilitating the convergence among cyberspace, physical space, and humans. As an inaugural execution and evaluation, this hierarchy evinced the significant tendency for evolving intelligent digital twins, motivating future research into the hierarchy's development to encompass human-centric and artificial intelligence in the most elaborate industrial environment. The notion of the digital triplet emerges as a consequence of this hierarchy's implication. Cultivating a hierarchy of perceptive digital twins, or aggregation, is one method for augmenting the four-level paradigm. The retrofitting paradigm will have its own digital triplet comprised of embedded digital twins from each layer. Digital triplet at an advanced level is an amalgam of digital twins at the previous level. By elucidating the functionality of pertinent information for each digital twin, complexity is diminished through interaction between numerous digital twins and human awareness. Eliminating complexity by segmenting a comprehensive digital triplet into facile digital twins with embedded functionality is a common framework called separation of concerns. This will enhance the sustainability and resilience of the industrial system and aggregate human-centricity as a critical factor of Industry I 5.0 with digital technologies [15,57–60].

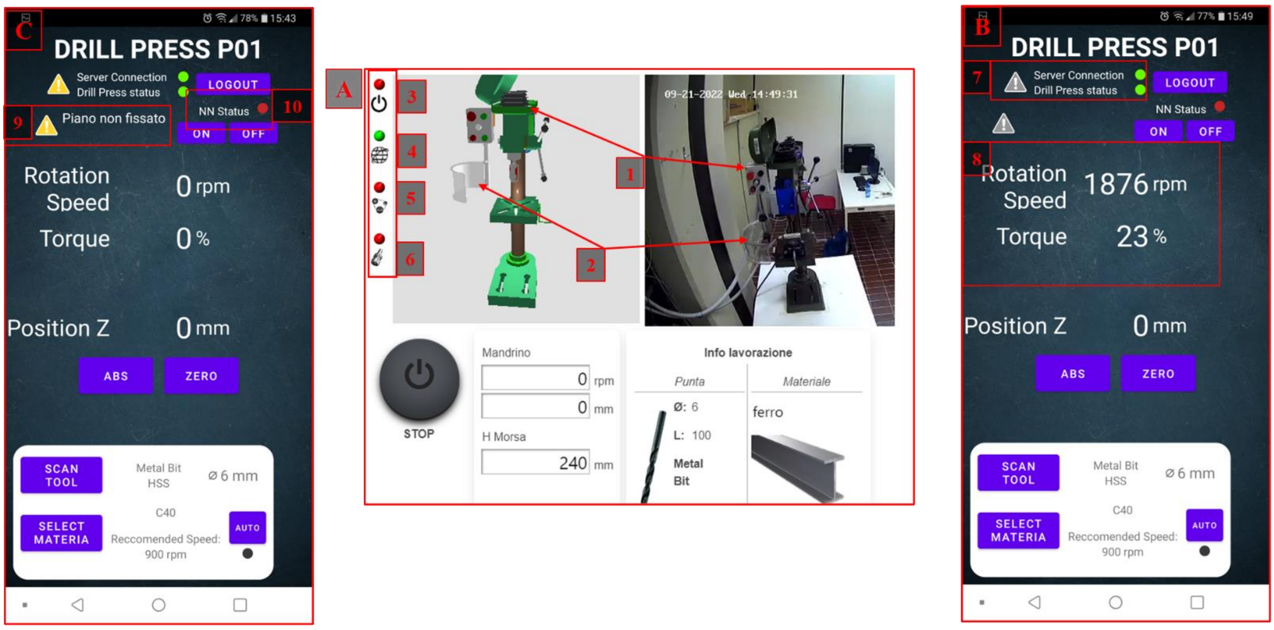

Figure 13. Real-time monitoring and anomaly detection in the cyber world. (**A**) Cyberworld in real-time: (**B**,**C**) Real-time anomaly detection via the Android App. 1 & 2. anomaly detection, 3. operating status, 4. Indicator of authentication, 5. Safety indicator, 6. IoT sensor and feeding sensor indicator. (**B**,**C**) Real-time anomaly detection via Android App: 7. Status indicators & App indicators, 8. The machining parameter, 9. Anomaly detection message. 10. Neural network status indicator.

5.6. Discussion

The four-level aggregation of the digital twins adduces the hierarchy needed for digital triplet D3 and the digital retrofitting paradigm into the bargain. Despite the fact that the research deliberates on a digital retrofitting paradigm, the hierarchy is devoid of the framework limitations and purveys all clarifications to overarching potential applications. The hierarchy is cultivated through the four levels of digital twins: the advanced level is volition for complex decision-making by deploying machine learning based on human ingenuity and creativity; domination for controlling the physical system's behaviour predictions and emulation; maturity for the iterative observation of the actual behaviour of the physical system using real-time data; and the trough level is sedentary for visualising and emulating virtual features through physical task awareness, in which the advanced level is an amalgam of digital twins at the previous level and the intervening communication is interspersed with the digital thread as an obfuscated layer amid all levels.

The hierarchy is dedicated to disclosing the intelligent activities based on the transformation and extraction of human awareness that are required to instigate the summit of the digital triplet paradigm by enhancing convergence and facilitating data and information interaction amid cyberspace, physical space, and humans. Deploying open-source facilities, digitalisation, and artificial intelligence technologies, such as IoT, MySQL—engine MariaDB data repository system, bidirectional full-duplex communication protocol Socket Io, Node.js. server, Python-based face recognition library, and Python-based open-source machine-learning library Scikit-learn. It imparts viability, security, and resilience and diminishes the elevated levels of financial risk required to instigate digital retrofitting. The facile intelligent digital twin enhances the efficiency of human–machine integration and improves expertise transformation through intelligent activities.

The hierarchy's usefulness as a digital triplet notion for digitisation was appraised for retrofitting a conventional drilling machine. The initial phase as a physical model of the proposed digital twin 'level 1' was adopted to be a typical drilling machine and retrofitted with sensors, open-source Arduino Mega 2560 and Arduino Nano 33 for IoT. The cyber-world 'level 2' comprised an evolved status that aggregates the surrogate model of the digital replica of the physical world. Sensor feedback from the physical assets was utilised to accomplish iterative observation. The proposed digital twin 'level 2' and 'level 3' comprised the three-dimensional model and real-time monitoring. The vibration failure and the anomaly detection were appraised by the incongruous vibration acquired in 'level 3'. Throughout each cycle of operation, the deployed perceptive digital twin with intelligent activities in 'level 4' was configured to monitor safety parameters and imply the decision for anomaly detection by demonstrating the online status of the machine with the Android App and web interface. The cybersecurity function and secure interface design were adopted in 'level 4' to ensure secure access control to unauthorised users for logging on to the digital triplet paradigm for both the cyber world of the machine and the Android App.

6. Conclusions

The paper annotated the four-level aggregation of digital twins needed for digital triplet D3 and the digital retrofitting paradigm. Despite the research's focus on digital retrofitting, the hierarchy was free of framework limits and clarified future uses. The hierarchy was cultivated through the four levels of advanced complex decision-making by deploying machine learning based on human ingenuity and creativity; domination for controlling the physical system's behaviour predictions and emulation; maturity for iterative observation of the actual behaviour of the physical system using real-time data; and the trough level is sedentary for visualising and emulating virtual features. The hierarchy revealed the intelligent activities based on the transformation and extraction of human awareness needed to instigate the digital triplet paradigm's summit by enhancing convergence and facilitating data and information interaction among cyberspace, physical space, and humans. It increases digital retrofitting's viability, security, and resilience and reduces financial risk. The intelligent digital twin improves human–machine integration and expertise transformation through smart activities. The appraisal demonstrated the viability of the digital triplet D3 hierarchy for retrofitting towards user-preferred intelligent solutions to leverage the ingenuity of human experts in collaboration with intelligent digital twins and to diminish the paradigm's complexity by interacting between several levels of digital triplet and human awareness and elucidating the functionality of pertinent information for each digital twin in all levels.

Author Contributions: Conceptualization, H.A.; Methodology, H.A.; Software, M.O.; Writing—original draft, H.A.; Writing—review & editing, H.A. and G.M.; Supervision, G.M., F.E.C. and M.B. All authors have read and agreed to the published version of the manuscript.

Funding: This paper is supported by European Union's Horizon Europe research and innovation programme under grant agreement No. 101057294, project AIDEAS (AI Driven industrial Equipment product life cycle boosting Agility, Sustainability and resilience).

Informed Consent Statement: Not applicable.

Acknowledgments: We are very grateful to the support by European Union's Horizon Europe research and innovation programme under grant agreement No. 101057294, project AIDEAS (AI Driven industrial Equipment product life cycle boosting Agility, Sustainability and resilience).

Conflicts of Interest: The authors declare no conflict of interest.

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