applied sciences

MDPI

Article

Identification Overview of Industry 4.0 Essential Attributes and Resource-Limited Embedded Artificial-Intelligence-of-Things Devices for Small and Medium-Sized Enterprises

Martin Barton [1,*], Roman Budjac [1,2,*], Pavol Tanuska [1], Gabriel Gaspar [1,2] and Peter Schreiber [1]

[1] Faculty of Materials Science and Technology in Trnava, Institute of Applied Informatics, Automation and Mechatronics, Slovak University of Technology in Bratislava, J. Bottu 2744/24, 917 24 Trnava, Slovakia; pavol.tanuska@stuba.sk (P.T.); gabriel.gaspar@uniza.sk (G.G.); peter.schreiber@stuba.sk (P.S.)
[2] Research Centre, University of Zilina, Univerzitna 8215/1, 010 26 Zilina, Slovakia
* Correspondence: martin.barton@stuba.sk (M.B.); roman.budjac@stuba.sk (R.B.)

Abstract: Nowadays there is a growing demand for small- and medium-sized enterprises (SMEs) to improve their level of digitalisation. This situation becomes even more critical in cases when SMEs act in the role of a subcontractor of large enterprises who demand the utilisation of certain digital operations. This paper aims to identify the essential Industry 4.0 attributes for the requirements of SMEs that enterprises can purchase to deploy an adequate solution with a view of increasing their competitiveness in the market. By analysing research articles and statistical data from the worldwide Web of Science database, we identify the major Industry 4.0 attributes for SME: Internet of Things (IoT), Big Data, Artificial Intelligence (AI), Cloud Computing, Simulation and Cybersecurity. Based on the review results and a survey by the European Commission, we propose devices primarily designed to implement AI tasks in industrial environments that meet the essential attributes for SMEs and have low entry costs. The subject of IoT is thoroughly addressed. Its subsets and the relationship between Industrial Internet of Things (IIoT) and Artificial Intelligence of Things (AIoT) are introduced and described. The characteristics of the listed devices as related to usability in the identified attributes are verified. Therefore, the description of the devices is provided with respect to their usability in SMEs. The main purpose of this paper is to identify attributes for SMEs and to develop strategic plans for the digitalisation requirements, particularly in the development of Artificial Intelligence as part of the implementation of the IoT pillar.

Keywords: Industry 4.0; Artificial Intelligence; Big Data; Smart Factory; resource-limited devices; AIoT; deep learning; edge AI

check for updates

Citation: Barton, M.; Budjac, R.; Tanuska, P.; Gaspar, G.; Schreiber, P. Identification Overview of Industry 4.0 Essential Attributes and Resource-Limited Embedded Artificial-Intelligence-of-Things Devices for Small and Medium-Sized Enterprises. *Appl. Sci.* **2022**, *12*, 5672. https://doi.org/10.3390/app12115672

Academic Editor: Antonella Petrillo

Received: 10 May 2022
Accepted: 31 May 2022
Published: 2 June 2022

1. Introduction

Industry 4.0 is considered to be the fourth industrial revolution and is characterised by smart manufacturing. It is a comprehensive and flexible system covering digital manufacturing technologies, network communications, computer technologies, automation technologies and many other areas. The fundamental of implementation is based on digital design and simulation, highly automated production, data from production processes and management of production processes, creating the whole process to gain knowledge from the production. On the other hand, Industry 4.0 is based on cyber–physical systems (CPS) using computing, communication and control technologies in close cooperation to achieve real-time intelligent manufacturing systems, dynamic control and information services. IoT, Big Data, AI, Augmented Reality, Simulation, Horizontal and Vertical Integration, Additive Manufacturing, Autonomous Robots, Cloud Computing and Cybersecurity are considered to be the key Industry 4.0 technologies [1]. Figure 1 shows a diagram of Industry 4.0 with the mentioned technologies.

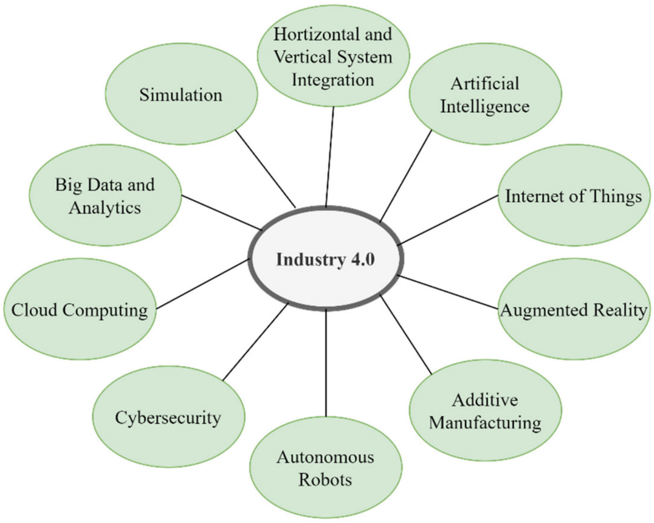

Figure 1. Industry 4.0 scheme.

Deploying all the Industry 4.0 technologies and moving the enterprise to the Smart Factory level is costly, time-consuming and personnel intensive. Large companies have adopted strategies for introducing digitisation into production, but the problem is represented by SMEs with a lack of capital and staff. Surveys show that SMEs are largely unaware of the need to introduce digitalization into production. In the future, such companies may lose their place in the market, as they will lose their competitiveness compared to large companies and small- and medium-sized digitised companies. If SMEs were to implement at least some of the key Industry 4.0 technologies, they could more easily sustain themselves in the market, speed up production and increase production capacity. This brings us to the main research question: Which key Industry 4.0 technologies should SMEs deploy? This could lead to a change in the adoption of business digitisation strategies in the future. In this article, we deal with the answer to this question. Research articles mainly focus on selected Industry 4.0 technologies that they describe as important from their perspective, which creates the space for this research. In our paper, we have focused on all the important Industry 4.0 technologies, and through a literature overview, we have identified the necessary attributes with a focus on SME. The importance of digitalisation for SMEs has also been declared by the European Commission, which has launched projects and conferences to support SMEs in the field of digitalisation.

The European Commission considers Artificial Intelligence to be the most important element of the Fourth Industrial Revolution, especially for small- and medium-sized enterprises. In second place in terms of importance and benefit, they consider Big Data analytics, and advocate a Business-to-Business strategy for implementing Big Data into practice. The European Commission sees huge potential in small- and medium-sized enterprises and emphasises the importance of transforming them into digital enterprises. With the deployment of AI in key areas, GDP is estimated to increase by around 1.8% by 2025, and in the longer term to result in a cumulative increase of 13.5% by 2030, depending on region and industry [2]. AI is likely to have the biggest positive impact on manufacturing—especially IIoT, mobility and smart healthcare. Achieving the best possible results will depend on harnessing the full potential of AI in SMEs.

This paper highlights the following:

1. identification of the necessary attributes of Industry 4.0 to move the SME to a level close to the Smart Factory,
2. highlighting the need for digitisation for SMEs,
3. proposing devices meeting the identified attributes of Industry 4.0 and their prospective use in SME.

In Section 2, we describe Big Data and AI as important tools that the European Commission considers to be the most important attributes of digitalisation. For identification of attributes, we used scientific articles from 2016 to 2022 in which the authors deal with the key attributes of Industry 4.0—this part is described in Section 2.3. In Section 2.4 we address the need for SMEs to transition to Industry 4.0. In Section 4, we describe IoT devices from an Industry 4.0 perspective. We identify the specific subcategories of IIoT and AIoT. Then, we compare the characteristics of selected specific devices with the identified Industry 4.0 attributes. The design of each device has been also compared in terms of the use of AI. All equipment has been selected to be prospective for SME use, with the priority assumption being low initial investment.

2. Materials and Methods

Based on the findings and recommendations of the European Commission, which identified Big Data and Artificial Intelligence technologies as key to the development and competitiveness of SMEs in the field of digitalisation. In the following section, we describe the two aforementioned technologies and their perspective in Industry 4.0. This section also includes a literature review with a methodological explanation of the research topic.

2.1. Big Data and Perspective in Industry 4.0

Big Data is one of the most important technologies in Industry 4.0. It includes the collection of data from all possible devices in companies as well as data on customers or processes. They contribute to increasing the quality and speed of production, predicting machine failures (predictive maintenance) and focusing production more on customer needs. The term Big Data does not only apply to the manufacturing sector, but it is also possible to collect and evaluate data in the business sector or in transport.

Big Data is characterised by the three Vs (Volume, Velocity and Variety). Volume, as the name suggests, predicts huge volumes of processed data, on the order of terabytes to tens of petabytes. Velocity characterises the speed of data recording and processing. Data are coming in at a great pace, so it is important to be able to process it continuously. The data are not only structured—some are semi-structured and some unstructured—this is characterised by the name Variety. In [3], the authors point out another important characteristic of data: the criticality and non-criticality of the collected data. Such data are particularly interesting for small- and medium-sized enterprises, as they usually have difficulty deploying Industry 4.0 technologies. Then, the question arises: Which data have a higher value when collected? The answer depends precisely on the criticality and non-criticality of the collected data, which contributes to an increase in the quality or speed of production.

For enterprises lacking sufficient capital to incorporate more technologies to enable the transition to Industry 4.0, Big Data is still a key technology to implement. The need to collect and analyse data is essential to ensure the competitiveness of businesses in their industries. In the case of small- and medium-sized businesses, Cloud Computing can also be a key in evaluating their collected data [4].

In this case, it is also necessary to be more concerned about the security of the data sent and evaluated in this way. To the same extent, key personnel should be trained in data collection and analysis [5]. Another problem for small and medium-sized enterprises can be the extensive data collection required for predictive maintenance. Predictive maintenance requires large amounts of time-consuming data for proper evaluation. This may not be a problem for large companies that own a higher number of machines. Small- and medium-sized enterprises, often having only a few, sometimes just one piece of machinery, may have difficulty accumulating enough data to properly evaluate predictive maintenance—in some cases it may take years [6]. Many companies collect data but cannot process and evaluate it efficiently. There is often a lack of departmental connectivity, where data from one department that could be used in other departments consequently remains unused because of the lack of an integrated system. The solution is Enterprise Resource Planning

(ERP) systems that work with all the data collected in the enterprise [7]. There are some of the challenges in deploying and operating Big Data in businesses.

2.2. Artificial Intelligence and Perspective in Industry 4.0

With the availability of computing power, it is possible to implement neural network models and create applications based on multi-perceptron, and it is possible to achieve accuracy of models deployed on production lines greater than 95%, which is difficult to achieve with classical methods. Some applications have been able to break this technological limitation and achieve accuracy of classification models in industrial applications of up to a 98% [8] recognition success rate. It should be emphasised that these models are dealing with a specific, clearly bounded problem, where the emphasis is on solving machine vision problems in a few well-defined categories rather than creating general-purpose machine recognition systems based on a large volume of data with many object categories. The same applies to the environment in which the product is located: it is precisely specified, and if it changes, it is only by the intervention of the operator within a precisely defined range, which greatly facilitates the design and testing of deep network models since the scene is not altered by random inputs but consists mainly only of the expected products that enter the scene on the production line. The environment itself, however, has its own specifics, with some technical features of the environment complicated the process. As mentioned earlier, the advantage is the stability and predictability of the environment in which the product is located, and the system subsequently works within it. The expected results are, of course, based on the nature of the industry's manufacturing environment, where the emphasis is primarily on the technical fulfilment of measurable milestones corresponding to customer orders. Another important aspect is the efficiency of production to ensure the competitiveness of the production mode. These insights further drive the requirements for a machine vision system that must be designed to adapt to the environment. This results in the inability of using the machine vision system/hardware created for an Industry 4.0 production environment for other uses, for example, for traffic density monitoring or other tasks. One of the long-term goals of the implementation of Industry 4.0 is, in our view, the design of Artificial Intelligence systems that will be hardware-universal, assuming modular system construction, and at the same time sufficiently powerful. Moving in this direction will be a dynamic element in machine learning implementation, especially for software, where it will be possible to change the deep learning model remotely.

Motivation behind Deep Learning Technology

Artificial intelligence algorithms have affected virtually the whole world of human activity in which an electronic device is used. Therefore, the collection of these data is possible. By post-processing and analysing the data, it is possible to design a model of machine learning (or deep learning) corresponding to the conditions that occur in real-life problems.

Intelligence at the edge is different from intelligence in the cloud in terms of requirements for energy, cost, accuracy and latency. Due to the limits of battery power and cooling systems in edge devices, energy consumption is strictly limited [9]. Worldwide, the high-tech industry invests an enormous amount of finance and effort into building a robust intelligent system based on neural networks in the expectation of solving technical problems with state-of-the-art accuracy. Areas using deep learning include machine vision, healthcare screening, personalised marketing, data analysis of social media customer preferences, predictive maintenance, anomaly detection, etc. Developing models with excellent results requires considerable time and power resources [10] to meet the high expectations.

All of the aforementioned circumstances have some aspects in common, namely the computing power and a large amount of data that comply with the highest accuracy to the statistical distribution of the dataset in the problem area being solved. The examined processes include compression of the model to an acceptable accuracy level, and, at the same time, sufficient model testing on selected embedded devices.

Embedded devices refer to the application-specific integration of computer hardware and software to satisfy the particular technical requirements of the system in which they are embedded. Based on the different applications of embedded systems, the respective global market can be segmented as automotive, consumer electronics, healthcare, telecommunication, industrial, homeland security and military, smart cities and aerospace [11–17].

In Figure 2 below, the curve depicts the relationship between societal expectations (on the vertical y-axis) through time (horizontal x-axis). It demonstrates the active application of technology in an industrial practice. This cycle represents the state of development and social exploitation of some technologies that have the potential to advance the whole society technologically [18]. It provides a graphical representation of new technologies in five phases: technology's start, peak of expectation, disillusionment, return to reality (reparation) and the last phase—the active application of technology in industrial practice.

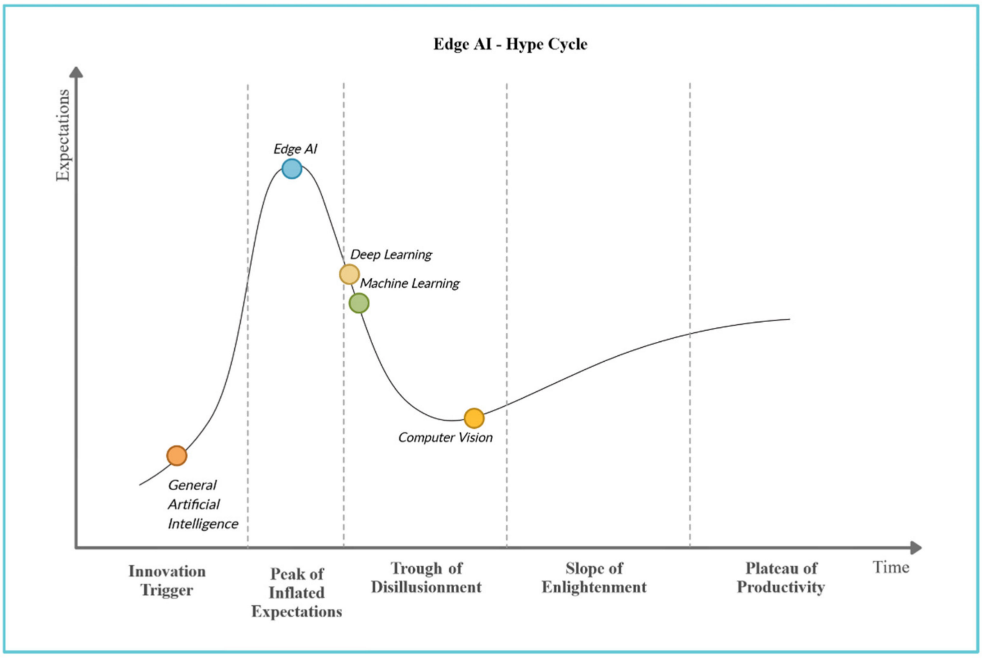

Figure 2. Technology trend cycle 2021.

2.3. Literature Review and Identification of Key Attributes of Industry 4.0 for SMEs

Identification of the correct essential attributes of Industry 4.0 is needed to find the answer to the research question: What specific technologies do SMEs need to put in place to move to a level close to that of a Smart Factory? Scientific studies from scientific databases from the last six years have been used to identify these attributes. Subsequently, the need for digitisation for small- and medium-sized enterprises is confirmed from scientific studies and a survey of the introduction of digitisation from December 2021. The articles highlight the benefits of digitisation summarised in the end of the chapter.

In [19], the authors identify nine main areas of Industry 4.0—Big Data and analysis, Optimisation and Simulation, Cloud Technology, Virtual Reality, Horizontal and Vertical Integration, IIoT, 3D printing, Autonomous Robotics and Cybersecurity. The authors emphasise the need to develop a framework to identify the urgency and benefits of implementing the identified attributes for companies, with each company and each industry needing different main attributes for implementation.

The review study [20], which compiled 161 highly cited articles, discusses Big Data, Data Intelligence and Artificial Intelligence as powerful and necessary tools in decision-making processes in companies. The authors highlight these three technologies as key to decision-making, prediction and integration and innovation in the manufacturing sector. Studies show that research has focused more on the intelligence of emerging technologies than on the use of human–artificial intelligence in decision-making.

A study monitoring the automotive industry [21] highlights Business Intelligence as the first major attribute of Industry 4.0, followed by Cloud Computing in order to increase the decision-making process that must be connected to the "Internet of Everything". The study highlights the need for adapting company policy based on customer needs. Other important attributes of Industry 4.0 are Big Data analytics and visualisation to support production quality and prediction.

The authors of [3] argue that the real implementation of Industry 4.0 presupposes a revolutionary change in its concept and design. Industrial processes will have to change radically from a traditional hierarchical model to a network model of interconnected services through data sharing and exchange. This highlights working with data as a central element in putting Industry 4.0 into practice. Therefore, it is necessary to pay particular attention to the security of the data collected. The article highlights two aspects that need to be considered when working with data:

1. volume, frequency, and diversity of data,
2. criticality or non-criticality of collected data [3].

On the other hand, in [22], the authors consider IoT, Artificial Intelligence and Machine Learning to be the key attributes of Industry 4.0. The real potential lies in the connection between computers and machines that can make decisions without the need for human intervention. They consider data handling, connectivity and digitisation to be the key elements for Industry 4.0 and Blockchain technology.

Study [23] discusses Blockchain technology as a powerful tool for supply chains in Industry 4.0. A Blockchain can bring traceability and transparency as major benefits. It can improve information security and trust and enhance efficiency. Future research in this area should focus on deploying Blockchain technology with IoT technologies and smarter contracts, and applying ML techniques to improve supply chain management. When choosing suppliers, price plays the biggest role from an economic point of view, environmentally friendly materials from an environmental point of view and health insurance at work from a social point of view if managers focus on flexibility [24].

According to the authors of [25], the implementation of the basic attributes of Industry 4.0 in medium-sized enterprises requires:

1. collection of all available data from the company's facilities,
2. protect data against unauthorised access,
3. evaluate usable data,
4. prepare employees for changes in companies.

To incorporate a more advanced Industry 4.0 strategy in medium-sized companies, it will be necessary to:

1. visualise data,
2. create a virtual representation of the entire system to identify and eliminate weaknesses in production,
3. design autonomous production systems [25].

The authors of the case study [26] incorporated data from four industries and evaluated the most important parameters of Industry 4.0 from economic, social and environmental points of view using a multi-context method that integrates a hesitant fuzzy set, cumulative prospect theory, and VIKOR for evaluating the degree of Industry 4.0 technologies. The results of the method are shown in the Figure 3 down below [26]. On x-axis, there are the individual technologies used in Industry 4.0, and the y-axis indicates the score with which these technologies ended up in the calculations. The data were used by industry as well as a World Economic Forum White Paper. They found that in the case of the manufacturing sector, the implementation of mobile technologies, namely 5G, cloud computing, sensors and drives and Big Data analytics, had the highest final value.

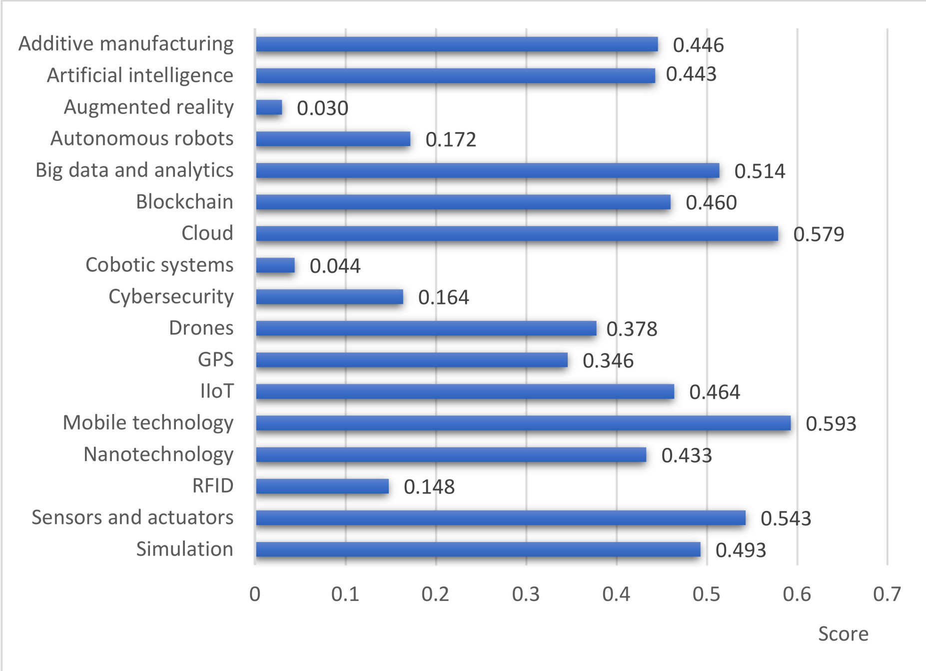

Figure 3. Study results comparing Industry 4.0 technologies.

In [5], using the Kaizen method, Big Data with analytics, Cloud computing, virtual simulation, and virtual reality are identified as key Industry 4.0 technologies, providing decentralisation, real-time capability, interoperability and virtualisation. The article shows how Lean Manufacturing practices are closely related to Industry 4.0 technologies.

The authors of [27] consider virtual reality, 3D printing and IoT to be the key technologies in Industry 4.0. They deal intensively with the education of students in these three areas and bring a methodology for incorporating them into school curricula. They point to the need to train new and retrain old workers in key areas of Industry 4.0.

A large survey [28] describes much of the Industry 4.0 technology—3D printing, Horizontal and Vertical Integration, Virtual Reality, Autonomous Robotics, Simulation, IIoT, CPS, Big Data analytics and Cybersecurity. The authors consider Horizontal and Vertical Integration to improve logistics and supply chains, robotics to increase productivity and quality and reduce production times, and Simulation, for instance a digital twin, to improve prediction. Among the strongest pillars are IIoT, especially with the support of 5G technology, Big Data analytics providing smart manufacturing and providing Business Intelligence to improve business models, and Cybersecurity to secure all production against external attacks. Implementing these technologies provides increased profits, a better supply chain and faster production.

Article [29] highlights Big Data and Cloud Computing as the key technologies of the Industry 4.0 concept. The use of both technologies is independent of the size of the company, and companies should include them in their business-innovation strategies. The authors would like to orient their future research to Big Data, with a focus on Cybersecurity. They emphasise the need to update existing Big Data standards and define new ones to ensure interoperability and complementarity.

Article [30] describes Big Data as a critical component for efficient work with data generated by CPS. Future research should focus on global design from data collection and processing to forecasting future events, optimisation and management, and production plans beyond CPS for Industry 4.0 objectives.

2.4. SMEs and Industry 4.0

Article [31] highlights the need for digitisation and transformation to the Industry 4.0 level for SMEs. It points to them as being the key contributors in the industry. Digitisation for small- and medium-sized enterprises needs to be further explored, as these enterprises often have limited resources and can be overtaken by large participants. The implementation of Industry 4.0 technologies will open up new possibilities and opportunities for these companies and make them more competitive in the industry. On the contrary, without implementation, difficulties in maintaining the industry can be expected.

A case study [32] focused on a local automotive company that implemented some Industry 4.0 attributes. The company:

1. implemented an ERP system as an internal and external platform for communicating with customers and suppliers and for improving decision-making processes (creation of the so-called "Digital factory"),
2. set up a multidisciplinary project team to improve products with customer input,
3. set up an integrated systems management unit to simplify the organisation and facilitate digitisation,
4. implemented logistics functions to improve responses to the international market,
5. set up staff training and set up a permanent training team [32].

Following the implementation of these attributes, revenue significantly increased and profits began to rise. Productivity and the resulting product quality have also increased significantly.

The results of [6] show great potential for small- and medium-sized enterprises if they cooperate and exchange data. For example, in predictive maintenance, a huge amount of data obtained from production is the key. For small- and medium-sized enterprises, obtaining such an amount of data can be a problem, and they need to collect data for many years. If small- and medium-sized enterprises work together, they can accumulate sufficient data and be competitive with large companies. This is not only true for predictive maintenance; the results of the study also show energy savings for individual companies in such data collection. On the other hand, security issues need to be addressed with such data exchange.

According to [4], by introducing Industry 4.0 technologies, SMEs can increase their organisational agility, adaptability and resilience to cope with a competitive environment. SMEs face three major challenges in terms of digitisation:

1. technological challenges—Industry 4.0 infrastructure is a major challenge for SMEs given the scale, resources and expertise needed to integrate it.
2. trust challenges—Research has shown that SMEs, if they could collaborate and share critical data with each other and with partners, would be able to gather the necessary amount of data faster, e.g., in terms of predictive maintenance. This would result in opportunities for asymmetric learning. On the other hand, business managers would find such cooperation difficult.
3. the Big Data challenges—as Industry 4.0 technologies generate and require the processing of vast amounts of data, SMEs may have difficulty storing, analysing and transforming data into efficient solutions [4].

As a framework to address these challenges, the authors suggest:

1. incorporation of Industry 4.0 technologies, especially Big Data and Cloud Computing. The Cloud can offer computing power to process large amounts of collected data at a reasonable price.
2. building a structure providing standards for interoperability between different technologies and suppliers and communication between different channels [33].
3. incorporation of communication protocols, security features on older systems and a set of uniform technical standards, providing a high level of credibility for SMEs in collaboration [4].

According to [34], Industry 4.0 technologies are created and used mainly by large companies; nonetheless, a large portion of suppliers are small- and medium-sized companies. In fact, 90% of registered companies in Europe are small- or medium-sized [34]. The authors identified problems with the implementation of Industry 4.0 technologies in small- and medium-sized enterprises in terms of finances and time needed to learn about these technologies. The results of the survey show that companies are interested in implementing Industry 4.0 technologies and digitisation. Big Data, Machine Learning, Autonomous Robots and an ERP or Manufacturing Execution System (MES) have been identified as technologies with great deployment and high complexity. They identified Sensors, Simulation, Predictive Maintenance and 3D printing as high-benefit, low-complexity technologies.

Article [35] explains the strategy for implementing Lean Manufacturing first, and then digitisation for SMEs. It describes that first it is necessary to focus the company's values on the customer, and only then start implementing individual technologies of Industry 4.0—first Big Data and Horizontal and Vertical Integration, then Simulation, Digital Twins and Artificial Intelligence. The article also found the benefit of greener production, as digitised businesses generate less waste.

Study [36] summarises surveys conducted on German companies. They found that a large number of companies are aware of the importance of digitisation, but as the size of companies decreases, so does the effort to deploy digitisation. SMEs make up the vast majority of all companies, and it is important that the gap between large and small- and medium-sized enterprises does not widen as large companies deploy digitalisation and have more potential/capital to deploy new technologies. The authors recommend that research should focus on reducing mistrust in new technologies, especially in the field of data security.

In [37], the authors highlight the need for companies to implement Industry 4.0 technologies. Businesses that implement these technologies are growing faster and have a better chance of surviving in the market. The authors identified the important aspects in the deployment of IoT in production. According to the results, companies deploying IoT in production should consider the criteria of technology, communication and safety in particular, with important sub-criteria of device heterogeneity, network security and hardware structure.

A survey [38] conducted with a sample of 125 respondents, of which one-third were small enterprises, one-third medium enterprises and one-third large enterprises, focused on the deployment of Industry 4.0 technologies as of December 2021 and showed alarming results. One of the results is the stagnation and decline of the introduction of digitisation in companies, where about half of the respondents stated that they had not yet started the Industry 4.0 application, one-fourth had started implementing it, and one-fourth of the respondents are working with Industry 4.0 teams. Over the last year, the perception of the need for digitisation has been declining—in 2020, 74% of respondents considered digitisation to be very important for the future, in 2021 there was a decrease to 46% of respondents. The survey shows that managers are a major barrier to digitalisation, which is clear evidence of stagnant digitalisation. Almost 66% of companies do not have an implementation strategy in place, 42% of companies have not started creating a strategy at all, and large companies have teams in charge of creating a strategy for implementing Industry 4.0 elements. Almost 77% of small- and medium-sized companies do not have an Industry 4.0 solution team. From the point of view of employee education, 30% of companies perceive the need for employee education in the field of digitisation. The companies see the biggest shortage of the required skilled workforce in the areas of system solutions for digitisation, artificial intelligence and industrial engineering and automation. From the results of the survey, small- and medium-sized enterprises can be expected to gradually lose orders due to their low competitiveness [38]. There is a need to improve awareness of digitisation and for companies to start creating and implementing their own strategies for the needs of transformation to the level of Industry 4.0.

3. Result of Identification of Key Attributes of Industry 4.0

The summarised studies and research clearly show the necessary attributes for the needs of digitisation and the shift of production of small- and medium-sized enterprises to a level close to that of a Smart Factory:

1. Big Data, which most of the research has evaluated as a key attribute in digitisation,

2. Artificial Intelligence, in connection with data processing and the expansion of production automation,
3. IoT, as a key element in data collection and processing,
4. Cloud Computing, especially needed for small- and medium-sized businesses to increase data processing and backup speeds, but large businesses can also benefit from it,
5. Simulation, especially creating a digital twin for predictive maintenance purposes,
6. Cybersecurity to protect data, either from outside attacks or from data loss.

Figure 4 shows an Industry 4.0 diagram for SMEs with the identified attributes.

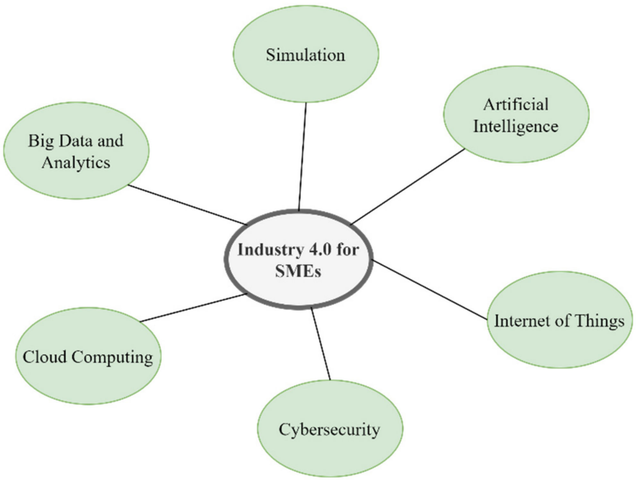

Figure 4. Industry 4.0 scheme for SMEs.

The remaining Industry 4.0 technologies are mentioned less frequently in the studies. Horizontal and Vertical System Integration is also possible to unify the systems used in companies and to share critical data more efficiently. By incorporating the mentioned technologies, companies could get significantly closer to the level of a Smart Factory, but for small- and medium-sized companies, it is still necessary to address the financial side and ensure the cheapest possible transition to Industry 4.0.

The results and references are summarised in Table 1.

Table 1. Quantity of individual attributes of Industry 4.0 marked as important in scientific articles.

Attributes	Quantity	References
Artificial Intelligence	6	Enyoghasi C., et al., 2021 [19], Saldivar A., et al., 2016 [21], Aoun A., et al., 2021 [22], Liebrecht C., et al., 2019 [25], Trappey A., et al., 2017 [33], Masood T., et al., 2020 [34]
Big Data	17	López Martinez P., et al., 2021 [3], Han H., et al., 2022 [4], Valamede L., et al., 2020 [5], Lazarova-Molnar S., et al., 2018 [6], Enyoghasi C., et al., 2021 [19], Di Vaio A., et al., 2022 [20], Saldivar A., et al., 2016 [21], Aoun A., et al., 2021 [22], Liebrecht C., et al., 2019 [25], Calderón R., et al., 2020 [27], Karnik N., et al., 2021 [28], Velasquez N., et al., 2018 [29], Trappey A., et al., 2017 [33], Masood T., et al., 2020 [34], Chen B., et al., 2018 [39], Lu Y., 2017 [40], Da Costa M., et al., 2019 [41]

Table 1. *Cont.*

Attributes	Quantity	References
IoT	11	Di Vaio A., et al., 2022 [20], Saldivar A., et al., 2016 [21], Liebrecht C., et al., 2019 [23], Bai C., et al., 2020 [26], Velasquez N., et al., 2018 [29], Trappey A., et al., 2017 [33], Sommer L., 2015 [36], Chen B., et al., 2018 [39], Lu Y., 2017 [40], Da Costa M., et al., 2019 [41], Thames L., et al., 2017 [42]
Horizontal and Vertical Integration	5	Calderón R., et al., 2020 [27], Menon S., et al., 2020 [31], Trappey A., et al., 2017 [33], Masood T., et al., 2020 [34], Lu Y., 2017 [40]
Cloud Computing	9	Han H., et al., 2022 [4], Valamede L., et al., 2020 [5], Lazarova-Molnar S., et al., 2018 [6], Enyoghasi C., et al., 2021 [19], Liebrecht C., et al., 2019 [25], Karnik N., et al., 2021 [31], Chen B., et al., 2018 [39], Lu Y., 2017 [40], Da Costa M., et al., 2019 [41]
Augmented Reality	2	Valamede L., et al., 2020 [5], Bai C., et al., 2020 [26]
Simulation	7	Valamede L., et al., 2020 [5], Aoun A., et al., 2021 [22], Liebrecht C., et al., 2019 [25], Calderón R., et al., 2020 [27], Trappey A., et al., 2017 [33], Masood T., et al., 2020 [34], Da Costa M., et al., 2019 [41]
Additive Manufacturing	2	Bai C., et al., 2020 [26], Trappey A., et al., 2017 [33]
Autonomous Robots	2	Calderón R., et al., 2020 [27], Trappey A., et al., 2017 [33]
Cybersecurity	6	Han H., et al., 2022 [4], Aoun A., et al., 2021 [22], Calderón R., et al., 2020 [27], Karnik N., et al., 2021 [28], Powell D., et al., 2021 [35], Sommer L., 2015 [36]

Figure 5 shows the number of articles in the Web of Science database for the year 2021 when single-individual attributes are entered as keywords. As the figure shows, the highest number of articles occurred when the Simulation attribute was entered, followed by AI, Big Data, Horizontal and Vertical Integration and IoT. The graph, like Table 1, confirms the importance of the identified attributes. The difference is visible in the attribute Cybersecurity, with 1588 articles. This number does not diminish the importance of the attribute but shows the need to focus scientific research on Cybersecurity.

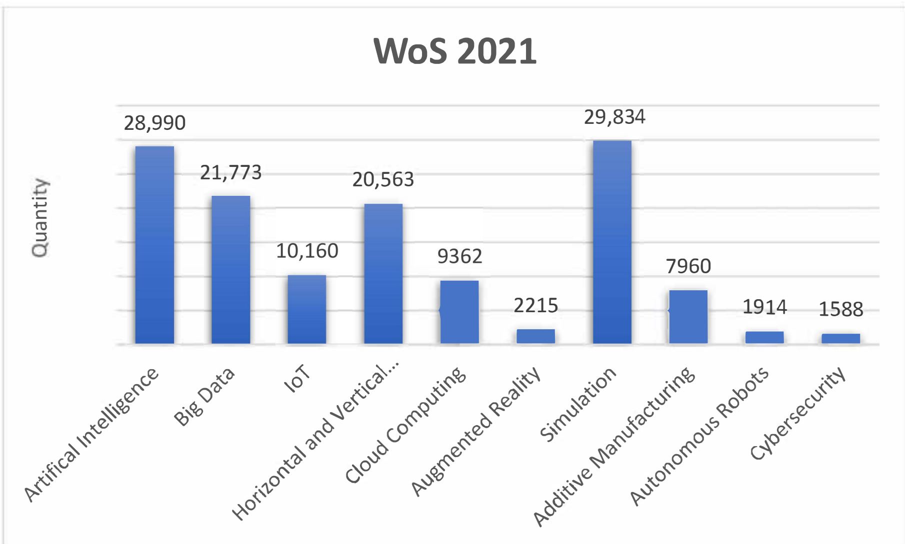

Figure 5. Number of articles mentioning attributes in the Web of Science database for 2021.

Benefits for Implementing Industry 4.0 for SMEs

There are not just financial benefits to deploying Industry 4.0 technologies and digitising businesses. A study [32] from 2017 described digitisation in an automotive company starting in 2006, from which the following figure comes. As the graph shows, the income of this company is marked in purple, and the operating profit from 2006 to 2016 is marked in green. The study performed was described above. The quality of the parts was not affected during the study, only the technologies of Industry 4.0 and organizational changes described above were deployed.

The Figure 6 shows that after the start of digitisation, income significantly increased year-on-year, especially since 2009, and profits began to jump sharply from 2014. This shows clear advantages in the implementation of Industry 4.0 technologies. Companies that decide to develop and implement a digitalisation strategy will benefit from it in the coming years. It is also already the case that if companies decide not to implement Industry 4.0 technologies, it may cost them a place in the market, and some such companies are likely to disappear in the near future as large companies and small- and medium-sized digitized enterprises overrun them. The benefits of digitisation for companies are more significant than the investment required to implement it. The benefits of digitisation and moving the company to the Smart Factory-level as determined from studies and surveys are as follows:

1. higher income,
2. higher profit,
3. increased quality of production,
4. increased productivity,
5. reduction of downtime,
6. greener production, digitised businesses generate less waste,
7. higher competitiveness of the company.

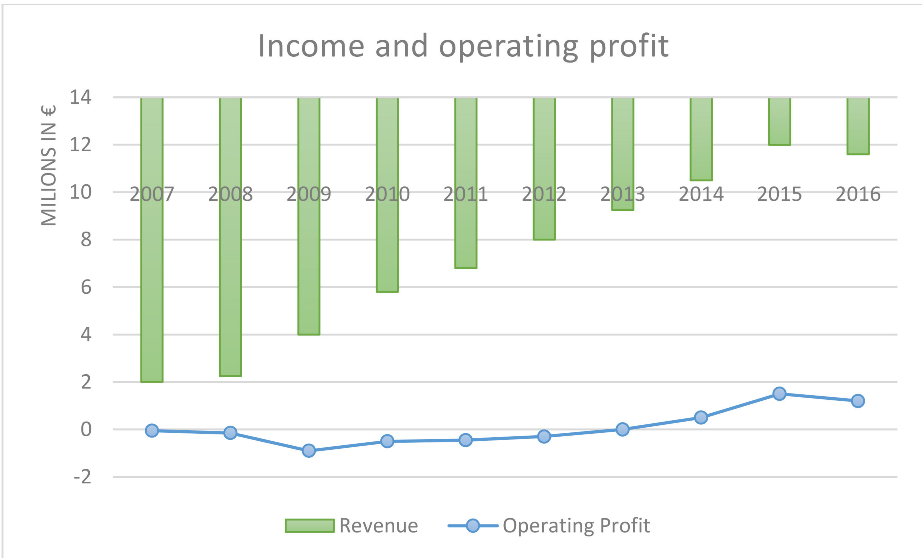

Figure 6. Income and operating profit after the start of digitalisation in an automotive company.

4. Perspectives on Embedded AIoT Devices for SMEs Based on Identified Attributes

The Industrial Internet of Things is a relatively new term in industry, often abbreviated as IIoT in the literature. A precise definition that could describe all the features of IIoT devices is very difficult. Boyes et al. [42] attempted to develop such a definition from a variety of sources [43,44]. Based on this knowledge, we can identify IIoT devices as IoT devices that meet industry standards and are oriented towards being applied in industrial manufacturing environments. Therefore, the aim of using these devices is to obtain data from industrial processes and subsequently evaluate these data to, for example, optimise production processes and predictive maintenance purposes, reduce the energy intensity of production and speed up or improve production. However, the application of IIoT devices is not limited to manufacturing sectors as part of the process of building a Smart Factory. IIoT devices are also integrated in other sectors where more detailed monitoring of existing equipment can bring benefits in the form of the ability to analyse the data and the subsequent ability to optimise the processes. The integration of such devices is therefore possible in various sectors of the economy where there is the possibility of measuring and collecting data, and it is not limited to supporting production processes. In the IIoT philosophy, intelligent machines are not only better at capturing and analysing data in real time than humans, they can also convey important information that can actually affect the speed and accuracy of decision making [45].

It also includes areas where there is very limited use of any kind of CPS, but where there is potential to extend technical means to support and optimise existing processes.

IoT devices are typically connectivity-aware, and an essential characteristic that is looked for in these devices is their ability to measure and transmit data to a higher-level system or within a vertical machine-to-machine (M2M) communication system. As with IoT devices, connectivity is extremely important for IIoT and AIoT. In this respect, a stable internet connection is essential, which is not a problem in the case of static production factories. In applications where it is not possible to provide a stable fixed connection to the Internet, or its installation is complicated and economically inefficient, the way to go is to connect using ultra-fast 5G modules to a high-speed 5th Generation network [46]. Such an extremely fast connection is essential for Deep Learning inference purposes. This need arises from the importance of transferring a reasonable amount of data from the AI processing system to the cloud server, mainly for model retraining, system maintenance and downloading new, modified deep learning models to the edge device.

Ensuring device connectivity is essential and is one of the pillars of Industry 4.0 deployment. When IoT devices are applied in various industries, it is very often necessary to ensure lower power consumption in the operating mode, and for this reason, in most cases they are single-board computers or microcontrollers for which the requirements for power consumption and compactness are balanced by the lower power required. Most IoT and IIoT devices do not require a lot of computing power because the requirements of their tasks do not require it. In the case of off-grid systems or IoT-embedded devices used in remote areas, such as stations collecting and transmitting environmental data [47–49], the use of AIoT is problematic because there is a limited source of electricity (or it depends on meteorological conditions e.g., photovoltaic systems [50] or wind systems [51]). Therefore, solutions to such applications focus on the use of ultra-low power embedded devices using microprocessors and microcontrollers [52]. The use of AIoT is problematic in cases of insufficient infrastructure at the installation site.

Due to the limitation of computer power at small scales, the possibilities for implementing deep learning application-based methods are also limited. Such a fundamental limitation, unlike business data analysis and server applications, does not allow the use of artificial intelligence algorithms on the edge, or only partially allows it with constraints.

The conditions we identified for the requirements of Industry 4.0 and the needs of SMEs for resource-constrained embedded devices for the purpose of this paper were as follows:

- reduced initial cost of embedded devices,
- hardware designed and software supported specifically for implementing AI on the edge,
- data mining support for Big Data purposes,
- the same development ecosystem for both prototyping and deployment devices,
- support for open-source AI frameworks,
- can be used for prototyping as well as for deployment,
- functionality supports the essential attributes of Industry 4.0,
- a known production and support cycle for individual devices.

Understandably, the need to use AI on the edge has created a gap for a new type of modified IoT devices and research that will reflect the needs of AI implementation in various industries. Since the generally observed trend is that the more complex the problem to be solved, requiring a complex problem-solving approach, the deeper the deep learning neural models required to achieve sufficient accuracy [53]. This fact leads to the further problem of generalising deep learning neural networks models [54]. To use Artificial Intelligence of Things, it is necessary to introduce approaches from the fields of IoT and Artificial Intelligence, as both are necessary attributes of Industry 4.0, as we identified in Section 3.

4.1. Deep Learning on Resource-Limited Devices

Based on the previous statements, it is obvious that tasks based on Artificial Intelligence using deep learning require specialised hardware. As is well known, computational tasks associated with deep learning need to be performed in parallel. The most appropriate means currently is the use of GPUs with a large number of cores or dedicated GPUs based on Tensor Processing Units (TPUs). Such hardware is not commonly available in IoT devices because the nature of their activities has not yet led to such a requirement. With the gradual drive to introduce Artificial Intelligence through deep learning as one of the pillars of Industry 4.0 transformation to industries, devices capable of processing deep network algorithms at the point of application—distributed AI—are also required [55]. This in turn creates a demand for compact embedded devices that would be able to use deep learning algorithms for their performance.

The relationship between IoT, IIoT and AIoT is shown in Figure 7. In our view, the relationship between them is synergistic, and each technological overlap of properties strengthens the contribution of the originally selected technology. This further highlights the need for multi-disciplinarity in device deployment when an AIoT device meets the industry standards. Its hardware architecture assumes the acceleration of deep neural networks, enables the use of Artificial Intelligence in industry [56,57] and meets connectivity requirements, the housing matches the requirements of the industrial environment, and it is an embedded device. These properties define IoT devices. Such devices are then able, in addition to the use of Artificial Intelligence, to perform a partial proxy function for other IoT devices, which are used, for example, as dataloggers [58] for data collection, but their performance is in the low-power range, on the order of the power of microprocessors or microcontrollers, and they have been specifically designed for a narrow profile of activity. AIoT devices have several orders more power because they are usually (but not necessarily) compact computers with a full-fledged OS. Then, such devices can also be used to partially replace other devices and take over their functionalities while continuing to perform their original purpose.

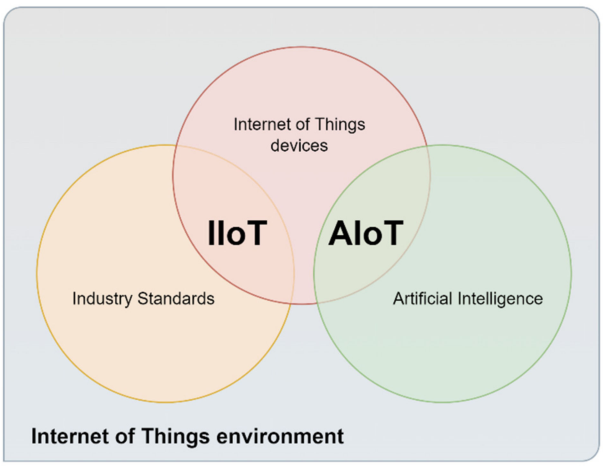

Figure 7. Relationship between AIoT and IIoT devices in IoT environment.

4.2. Verification of the Designed Devices Considering the Identified Essential Atrtibutes

As has been mentioned above, it is necessary to distil two other terms from the term IoT, namely Artificial Intelligence of Things and Industrial Internet of Things, for clarity of the issue. These two concepts fully complement the potential of IoT in industry, where by using AI on the edge it is possible to replace conventional methods with AI methods on the devices whose hardware architecture and software allow it. There are several devices that can be categorised as AIoT. Since there is no single standard and definition of such devices, we have based our definition on the attributes we have identified in Section 3. Among the devices we have turned much of our attention to is Nvidia's Jetson category of devices. These devices feature strong hardware architectures for acceleration of neural networks. Nvidia Jetson devices are designed to infer deep neural networks. They can also be categorised as AIoT based on their connection to the Internet or connection to an internal industrial network. The Jetson Nano and Jetson Xavier NX support network connectivity via Ethernet, Wi-Fi or even cellular communication (4G and now 5G cellular networks). Such a specialised architecture and connectivity enables the use of advanced real-time neural network model architectures.

Thus, in Table 2 we compare some of the characteristics of the devices from the perspective of Industry 4.0, whether they are promising for the fourth generation of industry, and if they meet the requirements for Industry 4.0 IoT, Big Data, AI, Augmented Reality, Simulation, Horizontal and Vertical Integration, Additive Manufacturing, Autonomous Robots, Cloud Computing and Cybersecurity.

Table 2. Evaluation of selected devices in terms of Industry 4.0 attributes.

Industry 4.0 Technologies	Jetson AGX	Jetson Xavier NX	Jetson Nano
IoT	Yes	Yes	Yes
Big Data	Yes	Yes	Yes
Artificial Intelligence	Yes	Yes	Yes
Augmented Reality	Yes	Yes	Yes
Autonomous Robots	Yes	Yes	Yes
Simulation	Yes	Yes	Yes
Horizontal and Vertical Integration	No	No	No
Additive Manufacturing	No	No	No
Cloud Computing	Yes	Yes	Yes
Cybersecurity	Yes	Yes	Yes

In Table 3, we evaluate the properties of selected devices that we selected as suitable for the implementation of AI on the edge and may be of interest to SMEs [59].

Table 3. Selected devices from an AI perspective for SME.

	Ultra Capacity Mobile Network (5G)	Supporting Open-Source A.I. Libraries	Native Deep Learning Acceleration	Housing Ready for Industry Application	Cloud Support	Producer Product Support	Power	Data Logging
Jetson AGX Industrial	After adjustment	Yes	Yes	Yes	Yes	No	40 W	Yes
Jetson Xavier NX	After adjustment	Yes	Yes	No	Yes	No	20 W	Yes
Jetson Nano	After adjustment	Yes	Yes	No	Yes	No	10 W	Yes

Despite numerous devices on the market explicitly suited for deep learning work, only a small percentage can be thought of as suitable. For our purposes we did not considered devices that are dependent on software support from the manufacturer, as this means the software ecosystem is closed, and only software supplied by the manufacturer can be used to exploit the potential of the device. Although such ready-made, comprehensive solutions are relatively quick to implement, we consider them to be expensive. We aimed to provide devices that are well-suited to prototyping task solutions while allowing the designed and tested solution to be implemented on the same platform. The second requirement that we considered significant was the support of open-source libraries for Artificial Intelligence software development, in particular OpenCV, Pytorch, Keras, etc., for seamless prototyping. Another requirement was a sufficiently long product lifecycle and support for ease-of-use and to ensure operability. The unity of the development ecosystem was also an important requirement in the case of using devices from different manufacturer's performance series. From the SME perspective, we were also interested in the initial entry cost, plus the flexibility of the devices for different purposes [60]. After careful consideration, we offer several devices, along with a description that characterizes them and explains their differences. These are the Nvidia devices that we have evaluated as a suitable solution considering the requirements mentioned above, plus others that arise to address the problems highlighted in this paper.

The selected characteristics are key from our point of view. By evaluating these characteristics, we want to find out which devices meet our technical characteristics in accordance with the identified attributes of Industry 4.0, considering the requirements of AI (hardware and software) and Big Data (collecting data).

Flexibility is a generally expected characteristics of technical systems. It is important to influence the flexibility of the system by design. Flexibility refers to how the deployed system can cope with and adapt to external changes that may occur during operation. From our point of view, flexibility in design and the ability to prototype devices and implement and test new neural network architectures and models is particularly interesting. Such experimental developments require wide flexibility in the early stages of design, and it is essential to react and adapt to external changes. Thus, it is not only about the flexibility of changing the created design by changing the parameters of the neural network model, but also about the possibility of creating your own prototype, either using your own libraries, or using some open-source libraries from available frameworks.

We can say that the Jetson series devices are viable for prototyping and at the same time for testing and deployment in a real production environment [61]. In addition, a major advantage besides flexibility in design, testing and deployment is their affordability, which we see as the key from an SME perspective [62].

For comparison, we selected a few devices with potential industrial applications that can use Artificial Intelligence to perform tasks using deep learning. Some of the presented/selected devices are prototype devices that are not intended for direct industrial use and do not meet industrial standards by their technical design. This problem can be solved by simply using available cases or by fabricating some additive-method (e.g., 3D printing) housing with the addition of a seal that would meet the resistance of enclosures required for electronic devices (IEC 60529) [63]. The need for the above solution is dependent on the classification of the environment in terms of regulations and standards (IEC 60721-3-3:2019) [64], which is determined by the designer. This classification is dependent on the legislation adopted in the country where the system is deployed. We did not consider the primary purpose of industrial deployment by the manufacturer of the embedded devices to be necessary, as such devices can be used in industry after the additional modifications mentioned above.

With the above selection of devices, we mainly wanted to highlight existing approaches to the use of deep learning in industry and possible new solutions and approaches that have the potential to establish themselves in the market. Hence, our endeavour has been to highlight the possibilities of using hardware ready for prototyping and implementing deep neural networks with respect to the needs of SMEs [65] and the attributes of Industry 4.0 identified in Section 3. The characteristics of selected devices in the context of Industry 4.0 are in Table 2.

We consider most prospective devices based on our assumptions above based on our selection of devices from the Nvidia Jetson family. This is due to the use of the already established and good hardware architecture of GPU cores and the partial use of tensor cores. The strength of Jetson devices is the native support for CuDNN libraries that feature kernel-optimised architectures such as ResNet, EfficientNet, SSD, MaskRCNN, Unet, VNet and more [66].

A significant advantage of using Jetson devices is that they all use the same software ecosystem [67]. Therefore, the same deep-model development process can be used for different ranges of applicability in terms of the required performance for a given application. Moving around in such a unified ecosystem is a great facilitator of development. The same process can be used for software development, and the same software tools can be used for both smaller and larger projects, as Nvidia Jetson provides devices with varying performance. Low entry costs facilitate initial prototyping, as the software model can be built and tested with very low entry costs before deployment. Possible extensions and changes can also be easily adapted, even if hardware performance needs to be increased, since, as we have described, all devices share a same development ecosystem. The development process will therefore be similar.

The Jetson Family does not just offer prototyping facilities in the form of Jetson Developer Kits. System-on-Module designs are suitable and recommended by the manufacturer for use in operation, i.e., not just prototyping devices. In the case of the high-performance AGX model, its design makes it directly ready for use in the industry. The Jetson AGX meets the industry standard with its design. The entire development environment is supported by the Nvidia NGC catalogue, with pre-trained, performance-optimised deep models, software containers and cloud support to facilitate custom deployments. You can then use the pre-trained model with your own real or synthetic data. Figure 8 showing Jetson software ecosystem.

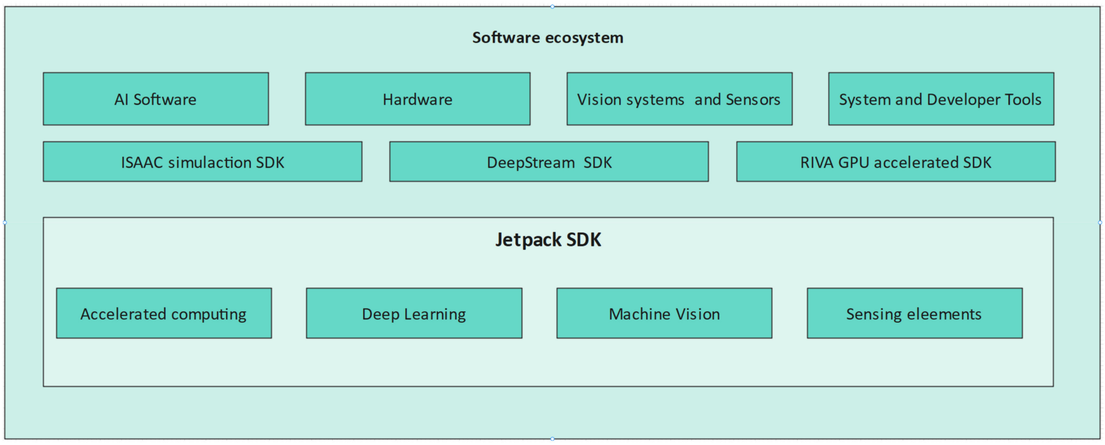

Figure 8. Jetpack Software ecosystem.

4.2.1. Jetson Nano

The Jetson Nano is built with a 64-bit quad-core Arm Cortex-A57 CPU running at 1.43 GHz alongside an NVIDIA Maxwell GPU with 128 CUDA cores capable of 472 GFLOPs (16 bits floating point) and has 4 GB of 64-bit RAM onboard along with 16 GB of eMMC storage and runs Linux for Tegra. The board size is 70 $\times$ 45 mm and has a 260-pin SODIMM connector supporting many interfaces, such as video, audio, USB. Jetson Nano is powered by micro-USB and consumes only 5 watts, and has extensive I/O ranging from GPIO to CSI.

NVIDIA also provides a Software Developer Kit (SDK) named Jetpack. Jetpack comprises many features: a board support package (BSP), Linux OS, NVIDIA CUDA and TensorRT software libraries for deep learning, computer vision libraries and GPU computing and multimedia processing. These capabilities enable multi-sensor Autonomous Robots, IoT devices with intelligent edge analytics and advanced AI systems. The SDK also includes the ability to natively install popular open source Machine Learning (ML) frameworks such as TensorFlow, PyTorch, Caffe, Keras and MXNet, along with frameworks for computer vision and robotics development such as OpenCV and ROS [68].

4.2.2. Jetson Xavier NX

An order of magnitude higher than the Jetson Nano is the Jetson Xavier NX. The Jetson Xavier NX has a powerful 384-core NVIDIA GPU based on the Volta architecture, and additionally features 48 tensor cores. The Jetson NX Xavier is powered by an input voltage of 19 V, which is a higher than that of the Jetson Nano. This is due to the more powerful hardware; hence, the overall power consumption of the Nano is lower than that of the Xavier. The higher power consumption is due to more powerful hardware, which provides the possibility to implement more complex neural network models, especially machine vision, allowing for applications such as robots or drones, etc. It is important to mention that development kits even in the case of the NX module are defined by the manufacturer as a non-production device. Still, it is ideal for prototyping and testing various deep learning techniques to solve defined problems. For comparison, the Jetson Nano has 472 GFLOPs and the Xavier NX has 21 TOPs.

There are several differences between Nano and Xavier in carrier board (kit) design, despite the fact that visually they are two similar products. At first glance, the use of active cooling is obvious in the case of the Xavier module. The Nano has a passive heatsink, but it is possible to attach additional active cooling to it or to replace it completely with an ICE Tower Cooling Fan [69]. The NX carrier board version has two M.2 Key slots—E,M—and the Nano has only one M.2 Key E socket to have the ability to connect via an external Wi-Fi card. This means that the Xavier has the option to attach fast, M.2 NVMe SSD external memory for running source code or just expanding storage. Unfortunately, you cannot use this drive to install an operating system image and boot from this drive. This is strictly possible only for the SD card—you must boot the operating system from it.

In terms of performance, the fundamental difference between Nano and Xavier is the use of INT8 precision tensor cores and the cumulative number of CUDA and tensor cores. Xavier has a Wi-Fi adapter installed from the factory, and the antennas are built-in on the underside of the plate carrier [70]. Thanks to this design, there is no need to additionally attach antennas, and they do not take up excess space outside the case as in the Jetson. Table 4 gives all necessary information about Jetsons.

Table 4. Jetson Nano and Jetson Xavier NX technical specifications.

Parameters	Jetson Nano B01	Jetson Xavier NX
GPU	128-core Maxwell	384 CUDA cores and 48 tensor cores
CPU	Quad-core ARM A57 1.43 GHz	6-core NVIDIA Carmel ARM 64-bit CPU
Memory	4 GB 64-bit LPDDR4 25.6 GB/s	8 GB 128-bit LPDDR4x 51.2 GB/s
Storage	MicroSD	MicroSD, M.2
Video Encoder	4 K @ 30 ∣ 4 × 1080 p–30 fps	2 × 4 K 30 fps, 6 × 1080 p–60 fps
Camera	2 × MIPI CSI-2	2 × MIPI CSI-2
Connectivity	Ethernet, M.2 Key E	Ethernet, M.2 Key E, M.2 Key M
Others	GPIO, I2C, I2S, SPI, UART	HDMI,4 × USB 3.1, USB 2.0 Micro-B, GPIO, I2C, I2S, SPI, UART

One of the weaknesses of the abovementioned models is that, although it is possible to use these devices after certain modifications, use in industry is not recommended by the manufacturer. This is the problem with most of the current cheap solutions that could be used as a basic solution for SMEs. While the Jetson Nano and Jetson Xavier pins, Asus T-inker, excel in prototyping solutions, their use in a real industrial environment is not recommended and would be done at users' own risk. In the case of production systems, such an experimental setup would require its own long-term testing of the reliability of the system in question.

4.2.3. Jetson AGX Industrial

AGX Industrial meets the necessary manufacturer's warranties. It can be deployed in locations with challenging conditions for application operations using AI at the edge. It therefore meets the expected industry standard that is sorely needed in the field of AI on edge devices, although independent testing is not yet available. It is made in two variants. The Jetson Xavier AGX Developer's kit [71,72] is suitable for prototyping and experimenting with the proposed solution. The second version is the aforementioned finished product ready to deploy the solution in industry.

As with the other Jetson devices, the Xavier AGX works with the same development ecosystem as Nano and Xavier NX: Jetpack for building AI-powered application. There is the possibility of using the Safety Extension Package to create an industrial application respecting the IEC 61508 and ISO13849 industry standards [73]. Another strong argument in favour of AGX Industrial is the product security, and thus the ability to create secure products. This includes, for example, the implementation of verified secure boot and hardware accelerated cryptography for encrypted storage and memory. One of the other key features is an operation lifetime guaranteed for 10 years [74]. This is especially important in terms of guaranteeing the functionality of the solution, repairability, serviceability and sustainability of the application that could work in an industrial environment. The key characteristics that Jetson AGX Industrial fulfils are clearly listed in Table 5. In terms of graphics performance, the AGX has 512 CUDA graphics cores and 64 tensor cores. The processor used is an 8-core NVIDIA Carmel Arm 8 MB L2 processor. This represents a performance of 30 TOPS, which is noticeably more than in the case of the Jetson Xavier NX. Detailed benchmark comparisons between the Jetson Xavier NX and Jetson AGX devices have been performed [75]. From the results, it is clear that, as expected, the Jetson AGX performed better on the pre-trained models. For instance, for the ResNet 50 Image classification, the AGX performed 1.7× better than the NX.

Table 5. Jetson Xavier AGX Industrial technical specifications.

Parameters	Jetson Xavier AGX Industrial
GPU	512 CUDA cores and 64 tensor cores
CPU	8-core NVIDIA Carmel 64-bit CPU 8 MB L2 + 4 MB L3
Memory	32 GB 256-bit LPDDR4x 36.5 GB/s
Storage	64 GB eMMC
Video Encoder	4 K–30 fps, 4 × 1080 p 30 fps, 9 × 720 p 30 fps
Camera	6 cameras
Connectivity	Ethernet, M.2 Key E
Others	USB 2.0 UART, SPI, CAN, I2C, I2S, DMIC & DSPK, GPIOs
Power	20 W–40 W

Table 6 summarizes the parameters that allow the Jetson AGX to be properly used in industry, with the following properties guaranteed: operating temperature and vibration, humidity and operating lifetime.

All presented devices meet the requirements to be a part of the proposed solutions in the field of Artificial Intelligence. The identified attributes are supported by these devices in all aspects. Jetson devices are included in the IoT device (or AIoT) category. These are low-powered, built-in devices that allow you to connect to the Internet and send or receive data as needed. In connection with the IoT pillar, there is also support for Cloud-Native technologies for rapid development. Jetpack also enables GPU accelerated containerized applications [76]. In the case of Cybersecurity, this is a very challenging area. In this area, in addition to IT systems, we recognize the threat of Artificial Intelligence algorithms "deceiving" a deep model on the basis of targeted input exchange to achieve incorrect evaluation of inputs by model parameters. The upcoming solution for the aforementioned devices is NVIDIA's open AI framework, Morpheus, for processing, filtering and classifying real-time data. [77]. The pillar of Artificial Intelligence is an integral part because the mentioned devices are specific for implementation in this area. The Big Data pillar is related to the previous pillars. The presented devices are able to collect and send data to the Cloud and thus fill the database with the obtained data for subsequent data analysis and evaluation. Simulation is partially supported. Jetpack includes the ISAAC Sim SDK, which provides a developer environment to create physically accurate simulations using synthetic datasets [78]. The use of the Jetsons in connection with Augmented Reality is possible. The task of these devices is to use them to identify objects in space using a camera [79–81]. From the name Horizontal and Vertical Integration, it is clear that this is not a technical feature of the embedded system; we can classify them as business strategies.

Table 6. Jetson Xavier AGX Industrial technical specifications.

Key Industrial Features	Jetson AGX Industrial
Operational Temperature	−40 °C to 85 °C at TTP
Vibration Operational	10–500 Hz, 5G RMS (random/sinusoidal) Non-operational: 10–1000 Hz, 3G RMS, 3-axis, FCT
Temperature	Operational: −40 °C to 85 °C at TTP
Humidity	Non-operational: 95% RH, −10 °C to 65 °C
Operating Lifetime	10 Years

5. Discussion

Available research clearly agrees with the need for digitisation for small- and medium-sized enterprises. The authors consider SMEs as key players in the market, but also as the most endangered by the need to digitise and thus improve their competitiveness compared to large companies. At the same time, surveys conducted in various countries point to the unpreparedness or even reluctance of more than half of SMEs to prepare a strategy to digitise them and upgrade them to the Smart Factory level, which could jeopardise the market soon as they do not run out of production capacity as a result of the growing demands for large companies using digitisation tools.

For these reasons, it is necessary for small- and medium-sized enterprises to create and implement strategies and plans for digitisation of their production environment and transformation to a level close to the Smart Factory. Digitisation is a major challenge for SMEs, whether financial, technological, or educational, and the three challenges are closely interlinked.

Probably the most important of these three challenges is the financial challenge, associated with the lack of capital needed to move the business to Industry 4.0. Small- and medium-sized enterprises cannot compete with large companies in terms capital, which is why digitalisation is a major problem for them. It could be solved by implementing only the attributes of Industry 4.0 needed to transform the company to a level close to the Smart Factory. If companies incorporate the necessary attributes, they will be able to profit from them and speed up and improve their production, which would increase their competitiveness in the market and thus increase profits. As an example, we illustrate predictive maintenance. If the company were able to effectively predict machine failures, it would be able to avoid them and could effectively use the time required for repairs for production, which would create less downtime.

The second big challenge is the technological challenge. Enterprises often have older machines from which it is difficult to obtain data [82]. These machines need to be replaced with newer IoT devices, or the old devices transformed via new devices/sensors to the IoT level needed for efficient data collection. Without the right technical equipment, transformation of companies to a level close to the Smart Factory will be difficult. Horizontal and Vertical System Integration is also part of this challenge if the company has several non-communicating systems. It is necessary to unify the systems either into one large system or to ensure the transfer of critical data between existing systems. In the case of critical data transmission, it will be necessary to analyse such data to start the integration process.

Collecting data from all sensors/facilities in the company and evaluating them can be difficult for small- and medium-sized enterprises. Therefore, it is also possible to determine the criticality and non-criticality of the collected data, as mentioned above, and to evaluate just such data. Data analysis needs sufficient computing power. Businesses have two options for dealing with this problem. The first solution is to use computers with sufficient performance and perform analysis in house, which can be costly in terms of investment and energy cost. The second solution is to invest in the Cloud, whereby the company would lease the performance from an intermediary. It is up to each business which of these two options they consider to be more beneficial.

The third challenge is the educational challenge. Businesses need to have people educated in new technologies and data analysis. They will either have to look for competent workers in the labour market or train their own employees from their ranks. People educated in the technologies, methods and procedures for implementing the Industry 4.0 concept will be critical for the industry in the near future according to a survey [38]. Secondary schools and universities will have to undergo changes and the incorporation of Industry 4.0 technologies into their curricula. At the same time, it also leads to the requirement to have qualified teachers in these areas. Competencies will also be needed in senior management positions in companies, and countries will have to approach and contribute to digitisation. The survey results also revealed that managers of SMEs who can make the decision to incorporate a digitalisation strategy are not aware of the importance of such an innovation in their enterprises. Two-thirds of the respondents stated that they had no opinion on the investment intensity of digitalisation, and half of the respondents had no opinion on the importance of Industry 4.0 applications [38]. It follows that there is a need to raise awareness of Industry 4.0, especially for SME managers, to realize the benefits of digitisation and the risks associated with the traditional way of production.

Identifying the essential attributes of Industry 4.0 is a great help for SMEs, especially in terms of investment and the complexity of digitalisation. Our solution offers the possibility to partially mitigate the high investment in increasing the level of digitalisation by implementing only the necessary attributes/technologies of Industry 4.0, which is also the subject of the first mentioned challenge. Our research also confirms the European Commission's assertion of the importance of implementing AI and Big Data in SMEs, but our findings expand the set of necessary attributes to include IoT, Cloud Computing, Simulation and Cybersecurity. The European Commission highlights a Business-to-Business strategy for working with data. Such a strategy requires sharing data between businesses, thus creating the need for the Cloud. With the creation of the Cloud and the need to send data, it is necessary to take care of the security of the data shared in this way—it is necessary to incorporate Cybersecurity. Big Data implies data mining, which is largely only possible from IoT devices. It follows that the attributes we have identified need to be incorporated into the solution that the European Commission for SMEs is working with.

For the second challenge, we have suggested the devices that meet the identified attributes of the Internet of Things and Artificial Intelligence and are also applicable for data collection in the area of Big Data. In the future, the third challenge of human resources and knowledge in the field of digitalisation will still need to be addressed. These devices are not off-the-shelf solutions, and it is therefore necessary to have specialists (developers) in the company capable of working with them. This brings us back to the importance of the third challenge. Their main advantage is their low entry cost, and compared to other IoT devices, they have high performance dedicated to AI tasks. There is a wide range of application possibilities, whether for prototyping or deployment solutions in manufacturing, transportation, agriculture, healthcare and more. Subsequently, we have described the selected devices, their hardware features and software support and compared them with each other. From the abovementioned findings, we have summarised the main benefits for SMEs and have explained why they are promising.

We present the offered devices as one of the possibilities, as there are many other manufacturers on the market, and other factors such as the geographical availability of products may also enter into the requirements for affordable embedded devices with the requirement for AI tasks. However, these are out of the scope of this paper. Thus, our proposed solution is not definitive and does not account for all requirements that may arise in individual use cases. In particular, it considers computing power for the needs of AI algorithms, usability in the implementation of Industry 4.0 attributes, low entry cost and versatility for implementing the application in different parts of production. By providing our own perspective on the issues addressed in this paper, we aim to contribute to the successful transformation of SME enterprises into a fourth-generation industry, which is closely related to the need to implement Artificial Intelligence on the edge in industrial manufacturing.

6. Conclusions

In this article, we focused on identifying the essential attributes of Industry 4.0 for SMEs and on advancing their level of digitalisation. We identified the attributes by analysing scientific articles and studies from the year 2016 to 2022. The technologies that SMEs should incorporate into digitalisation strategies are IoT, Big Data analytics, Artificial Intelligence, Cloud Computing, Simulation and Cybersecurity, which is the answer to the scientific question from the Introduction. If a company has several non-communicating systems, Horizontal and Vertical System Integration is added to the technologies for SMEs. From our analysis of the articles, Big Data has been identified as the most important Industry 4.0 technology. Big Data combines the other identified attributes. Data are collected from IoT devices, stored in repositories or in the Cloud and evaluated by Artificial Intelligence, and simulation is created from the data. The authors of the studies in the literature review were primarily concerned with Industry 4.0 technologies, which they identified as key; however, their research was not focused on SMEs. The main novelty in this paper is our approach to the topic, in that unlike the available articles, we have chosen to identify the essential attributes with respect to the needs of SMEs. As we have shown, the authors of the articles, the European Commission and the survey creators clearly agree on the importance and need to digitise SMEs, and in particular the fields of Artificial Intelligence and Big Data. This paper also proposed the types of interdisciplinary, specialized facilities suitable to implement deep learning algorithms in different industries. In the selection of these devices, we took into account the aspects resulting from the expectations for SMEs, such as low cost. We described each device from both a software and hardware perspective. We examined the suitability of the devices for their respective attributes for their use in Industry 4.0 transformation. We proposed three dedicated devices resource-limited to the use of AI on the edge. The Jetson Nano and Jetson Xavier NX devices are primarily suitable for prototyping, while the Xavier can also be used for solution deployment in certain circumstances. The third device was the Jetson Xavier AGX Industrial, which meets all industry standards for use in an industrial environment in addition to prototyping. With the support of the JetPack SDK software ecosystem, it is possible to use advanced Artificial Intelligence-based software design and implementation methods using NVIDIA support.

Therefore, it is essential to look for ways and methods to facilitate digitisation. We recommend focusing on the areas mentioned earlier and including these technologies in SME digitisation strategy plans. Digitisation is financially, technologically and personnel intensive. Nevertheless, as mentioned above, the benefits of digitisation far outweigh its challenges. Therefore, it is in the interest of businesses to embrace the digitalisation challenge.

Identifying the important attributes of Industry 4.0 allows us to focus our research for SMEs on the application of these attributes in enterprises. Therefore, we would like to focus on developing a platform for SMEs considering the identified attributes. The platform should offer a proposal for a possible solution to incorporate the mentioned attributes and help SMEs with the incorporation of a digitalisation strategy. As we mentioned, companies often have old machines from which data is difficult to mine. Part of our future work will be to propose possible solutions to upgrade old machines with IoT devices with respect to cost. The platform will include options for data mining, data processing, storage designs, Cloud solutions and the use of AIoT devices.

Author Contributions: Conceptualization, R.B., M.B., P.T., G.G. and P.S.; Data curation, M.B., R.B. and P.T.; Formal analysis, R.B., M.B. and G.G.; Funding acquisition, P.T.; Investigation, M.B. and R.B.; Methodology, R.B, M.B., G.G., P.S. and P.T.; Project administration, R.B. and M.B.; Resources, G.G., M.B. and R.B.; Supervision, R.B., G.G. and P.T.; Validation, P.T., G.G. and M.B.; Writing—original draft, M.B. and R.B.; Writing—review and editing, P.T., G.G. and P.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Operational Program Integrated Infrastructure and co-financed by the ERDF; grant number ITMS 313011W988: Research in the SANET network and possibilities of its further use and development. This paper was supported under the project of Operational Programme Integrated Infrastructure: Independent research and development of technological kits based on wearable electronics products, as tools for raising hygienic standards in a society exposed to the virus causing the COVID-19 disease, ITMS2014+ code 313011ASK8. The project was co-funded by European Regional Development Fund.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

1. Zhou, K.; Liu, T.; Zhou, L. Industry 4.0: Towards Future Industrial Opportunities and Challenges. In Proceedings of the 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), Zhangjiajie, China, 15–17 August 2015; pp. 2147–2152.
2. Industrial Applications of Artificial Intelligence and Big Data. Available online: https://ec.europa.eu/growth/industry/strategy/advanced-technologies/industrial-applications-artificial-intelligence-and-big-data_en (accessed on 3 March 2022).
3. López Martínez, P.; Dintén, R.; Drake, J.M.; Zorrilla, M. A Big Data-Centric Architecture Metamodel for Industry 4.0. *Future Gener. Comput. Syst.* **2021**, *125*, 263–284. [CrossRef]
4. Han, H.; Trimi, S. Towards a Data Science Platform for Improving SME Collaboration through Industry 4.0 Technologies. *Technol. Forecast. Soc. Chang.* **2022**, *174*, 121242. [CrossRef]
5. Valamede, L.S.; Santos Akkari, A.C. Lean Manufacturing and Industry 4.0: A Holistic Integration Perspective in the Industrial Context. In Proceedings of the 2020 9th International Conference on Industrial Technology and Management (ICITM), Oxford, UK, 11 February 2020; pp. 63–68.
6. Lazarova-Molnar, S.; Mohamed, N.; Al-Jaroodi, J. Collaborative Data Analytics for Industry 4.0: Challenges, Opportunities and Models. In Proceedings of the 2018 Sixth International Conference on Enterprise Systems (ES), Limassol, Cyprus, 1 October 2018; pp. 100–107.
7. Myrtveit, I.; Stensrud, E.; Olsson, U. Assessing the Benefits of Imputing ERP Projects with Missing Data. In Proceedings of the Seventh International Software Metrics Symposium, Oxford, UK, 4 April 2001; pp. 78–84.
8. Accurate Part Recognition, Location, and Guidance | Cognex. Available online: https://www.cognex.com/applications/customer-stories/other-industries/accurate-part-recognition-location-and-guidance (accessed on 12 April 2022).
9. Hoon Choi "Deep Quantization for Energy Efficient Inference at the Edge," a Presentation from Lattice Semiconductor. Edge AI and Vision Alliance. 2018. Available online: https://www.embedded-vision.com/platinum-members/latticesemi/embedded-vision-training/videos/pages/may-2018-embedded-vision-summit-cho (accessed on 15 April 2022).
10. Li, Y.; Wang, X.; Gan, X.; Jin, H.; Fu, L.; Wang, X. Learning-Aided Computation Offloading for Trusted Collaborative Mobile Edge Computing. *IEEE Trans. Mob. Comput.* **2020**, *19*, 2833–2849. [CrossRef]
11. Dong, S.; Wang, P.; Abbas, K. A Survey on Deep Learning and Its Applications. *Comput. Sci. Rev.* **2021**, *40*, 100379. [CrossRef]

12. Messaoud, S.; Bradai, A.; Bukhari, S.H.R.; Quang, P.T.A.; Ahmed, O.B.; Atri, M. A Survey on Machine Learning in Internet of Things: Algorithms, Strategies, and Applications. *Internet Things* **2020**, *12*, 100314. [CrossRef]
13. Zhou, L.; Zhang, C.; Liu, F.; Qiu, Z.; He, Y. Application of Deep Learning in Food: A Review. *Compr. Rev. Food Sci. Food Saf.* **2019**, *18*, 1793–1811. [CrossRef]
14. Ma, X.; Yao, T.; Hu, M.; Dong, Y.; Liu, W.; Wang, F.; Liu, J. A Survey on Deep Learning Empowered IoT Applications. *IEEE Access* **2019**, *7*, 181721–181732. [CrossRef]
15. Latha, R.S.; Sreekanth, G.R.R.; Suganthe, R.C.; Selvaraj, R.E. A Survey on the Applications of Deep Neural Networks. In Proceedings of the 2021 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 27 January 2021; pp. 1–3.
16. Wang, F.; Zhang, M.; Wang, X.; Ma, X.; Liu, J. Deep Learning for Edge Computing Applications: A State-of-the-Art Survey. *IEEE Access* **2020**, *8*, 58322–58336. [CrossRef]
17. Liu, J.; Xu, L.; Cao, X.; Zhang, K.; Zhang, Q.; Cai, Y. Review on the Architectures and Applications of Deep Learning in Agriculture. In Proceedings of the 2020 7th International Conference on Information Science and Control Engineering (ICISCE), Changsha, China, 18 December 2020; pp. 1234–1240.
18. Gartner Inc. *The 4 Trends That Prevail on the Gartner Hype Cycle for AI*. 2021. Available online: https://www.gartner.com/en/articles/the-4-trends-that-prevail-on-the-gartner-hype-cycle-for-ai-2021 (accessed on 9 May 2022).
19. Enyoghasi, C.; Badurdeen, F. Industry 4.0 for Sustainable Manufacturing: Opportunities at the Product, Process, and System Levels. *Resour. Conserv. Recycl.* **2021**, *166*, 105362. [CrossRef]
20. Di Vaio, A.; Hassan, R.; Alavoine, C. Data Intelligence and Analytics: A Bibliometric Analysis of Human–Artificial Intelligence in Public Sector Decision-Making Effectiveness. *Technol. Forecast. Soc. Chang.* **2022**, *174*, 121201. [CrossRef]
21. Saldivar, A.A.F.; Goh, C.; Li, Y.; Chen, Y.; Yu, H. Identifying Smart Design Attributes for Industry 4.0 Customization Using a Clustering Genetic Algorithm. In Proceedings of the 2016 22nd International Conference on Automation and Computing (ICAC), Colchester, UK, 7 September 2016; pp. 408–414.
22. Aoun, A.; Ilinca, A.; Ghandour, M.; Ibrahim, H. A Review of Industry 4.0 Characteristics and Challenges, with Potential Improvements Using Blockchain Technology. *Comput. Ind. Eng.* **2021**, *162*, 107746. [CrossRef]
23. Moosavi, J.; Naeni, L.M.; Fathollahi-Fard, A.M.; Fiore, U. Blockchain in Supply Chain Management: A Review, Bibliometric, and Network Analysis. *Environ. Sci. Pollut. Res.* **2021**. [CrossRef] [PubMed]
24. Fallahpour, A.; Wong, K.Y.; Rajoo, S.; Fathollahi-Fard, A.M.; Antucheviciene, J.; Nayeri, S. An Integrated Approach for a Sustainable Supplier Selection Based on Industry 4.0 Concept. *Environ. Sci. Pollut. Res.* **2021**. [CrossRef] [PubMed]
25. Liebrecht, C.; Krogmann, M.; Stricker, N.; Lanza, G. Methoden-Toolbox Zur Einführung von Industrie 4.0*/Method Toolbox for Implementing Industry 4.0—Development of a Methodology for the Identification and Evaluation of Industry 4.0 Potentials in Medium-Sized Companies. *J. Manuf. Syst.* **2019**, *109*, 216–222. [CrossRef]
26. Bai, C.; Dallasega, P.; Orzes, G.; Sarkis, J. Industry 4.0 Technologies Assessment: A Sustainability Perspective. *Int. J. Prod. Econ.* **2020**, *229*, 107776. [CrossRef]
27. Calderón, R.R.; Izquierdo, R.B. Machines for Industry 4.0 in Higher Education. In Proceedings of the 2020 IEEE World Conference on Engineering Education (EDUNINE), Bogota, Colombia, 15 March 2020; pp. 1–4.
28. Karnik, N.; Bora, U.; Bhadri, K.; Kadambi, P.; Dhatrak, P. A Comprehensive Study on Current and Future Trends towards the Characteristics and Enablers of Industry 4.0. *J. Ind. Inf. Integr.* **2021**, *27*, 100294. [CrossRef]
29. Velasquez, N.; Estevez, E.; Pesado, P. Cloud Computing, Big Data and the Industry 4.0 Reference Architectures. *J. Comput. Sci. Technol.* **2018**, *18*, e29. [CrossRef]
30. Xu, L.D.; Duan, L. Big Data for Cyber Physical Systems in Industry 4.0: A Survey. *Enterp. Inf. Syst.* **2019**, *13*, 148–169. [CrossRef]
31. Menon, S.; Shah, S. Are SMEs Ready for Industry 4.0 Technologies: An Exploratory Study of I 4.0 Technological Impacts. In Proceedings of the 2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM), Dubai, United Arab Emirates, 9 January 2020; pp. 203–208.
32. Moica, S.; Ganzarain, J.; Ibarra, D.; Ferencz, P. Change Made in Shop Floor Management to Transform a Conventional Production System into an "Industry 4.0": Case Studies in SME Automotive Production Manufacturing. In Proceedings of the 2018 7th International Conference on Industrial Technology and Management (ICITM), Oxford, UK, 7 March 2018; pp. 51–56.
33. Trappey, A.J.C.; Trappey, C.V.; Hareesh Govindarajan, U.; Chuang, A.C.; Sun, J.J. A Review of Essential Standards and Patent Landscapes for the Internet of Things: A Key Enabler for Industry 4.0. *Adv. Eng. Inform.* **2017**, *33*, 208–229. [CrossRef]
34. Masood, T.; Sonntag, P. Industry 4.0: Adoption Challenges and Benefits for SMEs. *Comput. Ind.* **2020**, *121*, 103261. [CrossRef]
35. Powell, D.; Morgan, R.; Howe, G. Lean First . . . Then Digitalize: A Standard Approach for Industry 4.0 Implementation in SMEs. In *Proceedings of the Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems*; Springer: Cham, Switzerland, 2021; pp. 31–39.
36. Sommer, L. Industrial Revolution—Industry 4.0: Are German Manufacturing SMEs the First Victims of This Revolution? *J. Ind. Eng. Manag.* **2015**, *8*, 1512–1532. [CrossRef]
37. Uslu, B.; Eren, T.; Gür, Ş.; Özcan, E. Evaluation of the Difficulties in the Internet of Things (IoT) with Multi-Criteria Decision-Making. *Processes* **2019**, *7*, 164. [CrossRef]
38. Industry4UM Evaluation of Industry 4.0 Survey in Slovak Republic in 2021. Available online: https://industry4um.sk/vyhodnotenie-prieskumu-industry-4-0-v-sr-2021/ (accessed on 16 March 2022).

39. Chen, B.; Wan, J.; Shu, L.; Li, P.; Mukherjee, M.; Yin, B. Smart Factory of Industry 4.0: Key Technologies, Application Case, and Challenges. *IEEE Access* **2018**, *6*, 6505–6519. [CrossRef]
40. Lu, Y. Industry 4.0: A Survey on Technologies, Applications and Open Research Issues. *J. Ind. Inf. Integr.* **2017**, *6*, 1–10. [CrossRef]
41. Da Costa, M.B.; Dos Santos, L.M.A.L.; Schaefer, J.L.; Baierle, I.C.; Nara, E.O.B. Industry 4.0 Technologies Basic Network Identification. *Scientometrics* **2019**, *121*, 977–994. [CrossRef]
42. Boyes, H. The Industrial Internet of Things (IIoT)_ An Analysis Framework | Elsevier Enhanced Reader. Available online: https://reader.elsevier.com/reader/sd/pii/S0166361517307285?token=CCD4C935CF533E9D04A0C18DB7FCDA780ACC95074E448D703BB615B13B183ECD0C7A0C4011D51766B72FC0F53099699E&originRegion=eu-west-1&originCreation=20220304133828 (accessed on 4 March 2022).
43. Dorsemaine, B.; Gaulier, J.-P.; Wary, J.-P.; Kheir, N.; Urien, P. Internet of Things: A Definition Amp; Taxonomy. In Proceedings of the 2015 9th International Conference on Next Generation Mobile Applications, Services and Technologies, Cambridge, UK, 9 September 2015; pp. 72–77.
44. Rose, K.A.; Sable, S.; DeAngelis, D.L.; Yurek, S.; Trexler, J.C.; Graf, W.; Reed, D.J. Proposed Best Modeling Practices for Assessing the Effects of Ecosystem Restoration on Fish. *Ecol. Model.* **2015**, *300*, 12–29. [CrossRef]
45. IIoT: Le Guide Complet Pour Bien Lancer Votre Projet, Ozone Connect, Toulouse. 2022. Available online: https://iotindustriel.com/actualites-et-evenements/ozone-connect-lance-le-1er-guide-iot-industriel-au-grand-maghreb/ (accessed on 6 May 2022).
46. Yarali, A. AI, 5G, and IoT. In *Intelligent Connectivity: AI, IoT, and 5G*; IEEE: London, UK, 2022; pp. 117–131, ISBN 978-1-119-68523-4.
47. Gaspar, G.; Dudak, J.; Behulova, M.; Stremy, M.; Budjac, R.; Sedivy, S.; Tomas, B. IoT-Ready Temperature Probe for Smart Monitoring of Forest Roads. *Appl. Sci.* **2022**, *12*, 743. [CrossRef]
48. Andreadis, A.; Giambene, G.; Zambon, R. Monitoring Illegal Tree Cutting through Ultra-Low-Power Smart IoT Devices. *Sensors* **2021**, *21*, 7593. [CrossRef]
49. Dudak, J.; Gaspar, G.; Sedivy, S.; Pepucha, L.; Florkova, Z. Road Structural Elements Temperature Trends Diagnostics Using Sensory System of Own Design. *IOP Conf. Ser. Mater. Sci. Eng.* **2017**, *236*, 012036. [CrossRef]
50. De Melo, G.C.G.; Torres, I.C.; de Araújo, Í.B.Q.; Brito, D.B.; de Andrade Barboza, E. A Low-Cost IoT System for Real-Time Monitoring of Climatic Variables and Photovoltaic Generation for Smart Grid Application. *Sensors* **2021**, *21*, 3293. [CrossRef]
51. Brunelli, D. A High-Efficiency Wind Energy Harvester for Autonomous Embedded Systems. *Sensors* **2016**, *16*, 327. [CrossRef] [PubMed]
52. Microcontrollers (MCU) and Microprocessors (MPU)—STMicroelectronics. Available online: https://www.st.com/en/microcontrollers-microprocessors.html (accessed on 1 April 2022).
53. Zhang, X.; Hu, M.; Xia, J.; Wei, T.; Chen, M.; Hu, S. Efficient Federated Learning for Cloud-Based AIoT Applications. *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.* **2021**, *40*, 2211–2223. [CrossRef]
54. Gorospe, J.; Mulero, R.; Arbelaitz, O.; Muguerza, J.; Antón, M.Á. A Generalization Performance Study Using Deep Learning Networks in Embedded Systems. *Sensors* **2021**, *21*, 1031. [CrossRef] [PubMed]
55. Janbi, N.; Katib, I.; Albeshri, A.; Mehmood, R. Distributed Artificial Intelligence-as-a-Service (DAIaaS) for Smarter IoE and 6G Environments. *Sensors* **2020**, *20*, 5796. [CrossRef]
56. Fan, Z.; Yang, W.; Wu, F.; Cao, J.; Shi, W. Serving at the Edge: An Edge Computing Service Architecture Based on ICN. *ACM Trans. Internet Technol.* **2021**, *22*, 1–27. [CrossRef]
57. Li, J.; Ma, R.; Mailthody, V.S.; Samplawski, C.; Marlin, B.; Chen, S.; Yao, S.; Abdelzaher, T. Towards an Accurate Latency Model for Convolutional Neural Network Layers on GPUs. In Proceedings of the MILCOM 2021—2021 IEEE Military Communications Conference (MILCOM), San Diego, CA, USA, 29 November 2021; pp. 904–909.
58. Aggarwal, M.; Zubair, M.; Unal, D.; Al-Ali, A.; Reimann, T.; Alinier, G. Fuzzy Identification-Based Encryption for Healthcare User Face Authentication. *J. Emerg. Med. Trauma Acute Care* **2022**, *2022*, 72. [CrossRef]
59. Singapore Energy Startups and SMEs Get AI Leg up from NVIDIA. Available online: https://www.nvidia.com/en-sg/deep-learning-ai/news/singapore-energy-startups-and-smes-get-ai-leg-up-from-nvidia/ (accessed on 27 May 2022).
60. Martikkala, A.; David, J.; Lobov, A.; Lanz, M.; Ituarte, I.F. Trends for Low-Cost and Open-Source IoT Solutions Development for Industry 4.0. *Procedia Manuf.* **2021**, *55*, 298–305. [CrossRef]
61. Jian, M.-S.; Pan, C.-J. Blockchained Industry Information Handoff Based on Internet of Things Devices with Intelligent Customized Object Recognition. *Sensors* **2022**, *22*, 2312. [CrossRef]
62. Hansen, E.B.; Iftikhar, N.; Bøgh, S. Concept of Easy-to-Use Versatile Artificial Intelligence in Industrial Small & Medium-Sized Enterprises. *Procedia Manuf.* **2020**, *51*, 1146–1152. [CrossRef]
63. IEC 60529:1989+AMD1:1999+AMD2:2013 CSV | IEC Webstore | Water Management, Smart City, Rural Electrification. Available online: https://webstore.iec.ch/publication/2452 (accessed on 8 April 2022).
64. Standards, E. BS EN IEC 60721-3-3:2019 Classification of Environmental Conditions Classification of Groups of Environmental Parameters and Their Severities. Stationary Use at Weatherprotected Locations. Available online: https://www.en-standard.eu/bs-en-iec-60721-3-3-2019-classification-of-environmental-conditions-classification-of-groups-of-environmental-parameters-and-their-severities-stationary-use-at-weatherprotected-locations/ (accessed on 8 April 2022).
65. Feng, H.; Mu, G.; Zhong, S.; Zhang, P.; Yuan, T. Benchmark Analysis of YOLO Performance on Edge Intelligence Devices. *Cryptography* **2022**, *6*, 16. [CrossRef]

66. Song, W.J. Chapter Two—Hardware Accelerator Systems for Embedded Systems. In *Advances in Computers*; Hardware Accelerator Systems for Artificial Intelligence and Machine Learning; Kim, S., Deka, G.C., Eds.; Elsevier: Amsterdam, The Netherlands, 2021; Volume 122, pp. 23–49.
67. Jetson Software. Available online: https://developer.nvidia.com/embedded/develop/software (accessed on 6 May 2022).
68. Nvidia Corporation NVIDIA Jetson Linux Developer Guide: Introduction | NVIDIA Docs. Available online: https://docs.nvidia.com/jetson/l4t/ (accessed on 22 April 2022).
69. EP-0113—52Pi Wiki, Datasheet. Available online: https://wiki.52pi.com/index.php/EP-0113 (accessed on 15 April 2022).
70. Jetson Xavier NX. Available online: https://developer.nvidia.com/embedded/jetson-xavier-nx (accessed on 25 April 2022).
71. Nvidia Corporation User Guide JETSON AGX XAVIER DEVELOPER KIT. 2018. Available online: https://siliconhighway.com/wp-content/gallery/jetson-xavier-nx-datasheet-us-1154975-r4-web-original.pdf (accessed on 29 April 2022).
72. NVIDIA Jetson AGX Xavier Developer Kit Carrier Board. Available online: https://siliconhighway.com/wp-content/gallery/SP-09778-001_v2.0.pdf (accessed on 20 March 2022).
73. NVIDIA Jetson AGX Xavier Industrial | Datasheet. Available online: https://siliconhighway.com/wp-content/gallery/SP-09778-001_v2.0.pdf (accessed on 20 March 2022).
74. Barrie Mullins NVIDIA Unveils Jetson AGX Xavier Industrial Module. Available online: https://blogs.nvidia.com/blog/2021/06/15/jetson-agx-xavier-industrial-use-ai/ (accessed on 25 April 2022).
75. Jetson Benchmarks. Available online: https://developer.nvidia.com/embedded/jetson-benchmarks (accessed on 25 April 2022).
76. Cloud-Native on Jetson. Available online: https://developer.nvidia.com/embedded/jetson-cloud-native (accessed on 25 April 2022).
77. NVIDIA Morpheus AI Cybersecurity Framework. Available online: https://developer.nvidia.com/morpheus-cybersecurity (accessed on 26 April 2022).
78. Monteiro, F.F.; Vieira-e-Silva, A.L.B.; Teixeira, J.M.X.N.; Teichrieb, V. Simulating Real Robots in Virtual Environments Using NVIDIA's Isaac SDK. In Proceedings of the Anais Estendidos do Simpósio de Realidade Virtual e Aumentada (SVR); Sociedade Brasileira de Computação—SBC, Rio de Janeiro, Brazil, 16 October 2019; pp. 47–48.
79. Sabeti, S.; Shoghli, O.; Baharani, M.; Tabkhi, H. Toward AI-Enabled Augmented Reality to Enhance the Safety of Highway Work Zones: Feasibility, Requirements, and Challenges. *Adv. Eng. Inform.* **2021**, *50*, 101429. [CrossRef]
80. Gilles, A. Real-Time Embedded Hologram Calculation for Augmented Reality Glasses. In Proceedings of the 2021 International Conference on Visual Communications and Image Processing (VCIP), Munich, Germany, 5 December 2021; pp. 1–5.
81. Ferraz, O.; Menezes, P.; Silva, V.; Falcao, G. Benchmarking Vulkan vs OpenGL Rendering on Low-Power Edge GPUs. In Proceedings of the 2021 International Conference on Graphics and Interaction (ICGI), Porto, Portugal, 4 November 2021; pp. 1–8.
82. Bellavista, P.; Bosi, F.; Corradi, A.; Foschini, L.; Monti, S.; Patera, L.; Poli, L.; Scotece, D.; Solimando, M. Design Guidelines for Big Data Gathering in Industry 4.0 Environments. In Proceedings of the 2019 IEEE 20th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM), Washington, DC, USA, 10 June 2019; pp. 1–6.