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Industrial Internet of Things: Requirements, Architecture, Challenges, and Future Research Directions

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ABSTRACT Industry 4.0 relates to the digital revolution of manufacturing and other sectors, such as retail, distribution, oil and gas, and infrastructure. Meanwhile, the Industrial Internet of Things (IIoT) is a technological advancement that leads to Industry 4.0 implementation by boosting the manufacturing sector's productivity and economic impact. IIoT provides the ability to provide global connectivity between components in different locations. The manufacturing sector has had various difficulties implementing IIoT, primarily due to IIoT characteristics. This paper offers an in-depth review of Industry 4.0 and IIoT, where the primary motivation behind this is to introduce the most recent advancements related to Industry 4.0 and IIoT, as well as to address the existing limitations. Firstly, this paper presents a novel taxonomy of IIoT challenges that includes aspects of each challenge, such as the terminology and approaches utilized to solve these challenges. Besides IIoT challenges, this survey provides an in-depth demonstration of the many concepts related to IIoT, such as architecture and use cases. Secondly, this paper provides a comprehensive review of the state-of-the-art of Industry 4.0 in terms of concepts, requirements, and supporting technology. In addition, the correlation between enabling technology and technical requirements is discussed in detail. Finally, this paper highlights deep learning, edge computing, and big data as key techniques for the future directions of IIoT. Furthermore, the presented techniques are thoroughly examined to present an alternative method for future adoption. In addition to the showcased techniques, a new architecture for the future of IIoT based on these three primary techniques is also proposed.

INDEX TERMS Industry 4.0, IIoT, deep learning, edge computing.

I. INTRODUCTION

The digital transition of manufacturing and other sectors such as retail, logistics, oil, and gas, and infrastructure are referred to as Industry 4.0 [1]. The bridging between the real and digital ‘‘cyber-physical networks’’ is an obvious feature of Industry 4.0. The partial transition of automated decision-making to cyber-physical devices and computers is part of Industry 4.0 [2]. Industry 4.0 brings together the cutting-edge technological technologies like big data [3], artificial intelligence (AI) [4], and the Internet of Things (IoT) [5], [6]. Digital transformation will lead to the creation of ‘‘smart factories,’’ which learn and respond to new demands using data from linked operations and production systems [1]. Newmarket and manufacturing models, marketplace norms, and technologies are being established as part of Industry 4.0 enabling top-performing suppliers to distinguish themselves from their rivals [5]. Intelligent automation and analytics can be combined to create a sustainable and effective production environment [2]. Manufacturers can use Industry 4.0 to help them meet their goals for financial performance growth, business system modernization, improved customer service, and new products and services [5]. Processes, business models, and even the way manufacturing and distribution are done have all had to evolve as a result [2]. Industry 4.0 is similar to digital transformation because it is not a one-time event. Businesses need a systematic, staged strategy that may begin with small projects and progress to more creative, advanced, and aggressive initiatives [1], [2]. Leading organizations will enhance their operations across

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TABLE 1. List of abbreviations.

Abbreviation	Definition
IoT	Internet of Things
IIoT	Industrial Internet of Things
AI	Artificial Intellegence
ML	Machine Learning
DL	Deep Learning
M2M	Machine-to-Machine
H2M	Human-to-Machine
CPS	Cyber Physical System
CPPS	Cyber Physical Production System
AR	Augmented Reality
P2P	Point-to-Point
6LoWPAN	IPv6 over Low-Power Wireless Personal Area Networks
QoS	Quality of Service
RDF	Resource Description Framework
URL	Uniform Resource Locator
HDFS	Hadoop Distributed File System
SDN	Software-Defined Networking
5G	Fifth-Generation Technology Standard for Broadband Cellular Networks
MQTT	MQ Telemetry Transport
CoAP	Constrained Application Protocol
EWS	Exponential Windowing Scheme
WoT	Web of Things
ETL	Extract- Transform- Load
AP	Access Point
PCA	Principal Component Analysis
LTE	Long-Term Evolution
ANN	Artificial Neural Network
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Units
WSN	Wireless Sensor Network
FL	Federated Learning
ASIP	Application Specific Instruction Processor
FPGA	Field Programmable Gate Array
MCC	Mobile Cloud Computing
MEC	Mobile Edge Computing

the board by restructuring, which involves streamlining procedures to maximize efficiency, strengthening teamwork across the enterprise and supply chain, and providing goods to extend their customer base [5]. Manufacturing is evolving at a pace and scale that rivals the introduction of steam power or software-driven automation [1]. The consequences of this digital revolution have been important, and their promise is still enormous [2]. According to Gartner, the markets for many main Industry 4.0 products (advanced cybersecurity, virtual reality) are estimated to be worth between 150 and 200 billion dollars [7].

Relevant technical advances have been prioritized as a part of the transition to Industry 4.0. Relevant technical advances have been prioritized as a part of the transition to Industry 4.0. Artificial intelligence, big data, Internet of Things convergence, cyber-physical networks, and other innovations are among these technologies [1]. The Internet of Things combines the real and digital worlds, greatly extending the possibilities of information technology [8]. By utilizing IoT, we can electronically track and control our' ' things'' by integrating physical assets with the digital sphere using sensors and actuators. The IoT has emerged as one of the most significant inventions of the 21st century in recent years [6]. Now we can link everyday objects to the internet through embedded devices, such as kitchen appliances, vehicles, thermostats, and baby monitors, seamless connectivity between individuals, processes, and staff is possible. Physical things can exchange and gather data with limited human interference because of low-cost storage, the cloud, big data, analytics, and mobile technology [9]. Digital platforms can log, track, and change each connection between connected objects in today's hyperconnected world.

The Industrial Internet of Things (IIoT) is a technical development that increases the manufacturing and economic effect of the manufacturing sector [10], [11]. IoT features, such as sensing, actuating, interconnecting, and processing data at various stages have resulted in the technological advancements listed. Data collection, processing, and intelligent decision-making with minimal human involvement are skills and advantages that IIoT systems offer to manufacture environments. IIoT is a division of the Internet of Things that focuses on the manufacturing industry [11]. IIoT focuses on enhancing manufacturing enterprises' accessibility, performance, scalability, time savings, and cost savings and is often correlated with Industry 4.0 [12]. The traditional production environment relies heavily on local interaction between system components [10]. IIoT will easily overcome locality due to its ability to provide global communication between components located in different locations [11]. The manufacturing industries have faced various difficulties in adopting IIoT; these challenges are mainly due to the IoT characteristics themselves [11]. IIoT issues are not inherently different from those related to IoT, depending on the interaction between IIoT and IoT. The most prominent IoT features include limited memory space, low energy consumption, wireless networking, and computing capability [11], [12]. Regardless of other factors and challenges, the IoT characteristics affect on implementing and sustaining IIoT infrastructure.

A. METHODOLOGY

The survey's methodology includes gathering and evaluating a list of academic publications published as conference papers or journal articles using open APIs from academic databases and search engines such as IEEE Xplore, Scopus, and Web of Science. The following are the steps involved in gathering these works.

1) The method begins by searching for the keywords " Industry 4.0 – IIoT " in each search engine listed above to find the most relevant work.
2) Examine the following topics of the gathered articles:
   a) The architecture and challenges of the IIoT were discussed.
   b) Future research directions and strategies for addressing existing difficulties.
   c) Industry 4.0 and its interaction with IIoT.
3) To increase the predicted contribution in this survey, we try to limit the most of publication date to within the previous five years.

4) Consequently, we collected 113 publications that matched all of the search criteria and were included in this survey.

Collected articles have been analyzed and reviewed according to their type and contribution to constructe the sections of this survey.

B. RELATED WORK AND CONTRIBUTION

Several reviews on IIoT were presented recently, each covering different aspects of IIoT. The survey in [13] discusses several characteristics of IIoT. The survey examines concepts such as IoT, IIoT, and Industry 4.0, concluding that these terms should not be used interchangeably. The study then investigates many suggestions for IIoT design and introduces one that attempts to graphically depict the complexity of IIoT hybrid architecture. In addition, survey covers some basic topics like connection and standards. Finally, the important challenges are addressed, including energy efficiency, real-time performance in dynamic contexts, the requirement for coexistence and interoperability, and application security. Interoperability, security and privacy, scalability, heterogeneity, dependability, and resource management are some of the technological challenges that have been considered.

In [14], the survey begins with a review of several structures for underlying IIoT processes and a proposal for their layered design. Then, in addition to analyzing existing data management solutions for IIoT, a survey illustrating the operation of various IIoT communication protocols. Enabling technology is will addressed in this survey, including IoT, cloud computing, big data analytics, artificial intelligence, cyber-physical systems, augmented reality, virtual reality, Humane-to-Machine (H2M), and M2M communication.

In [15], recent applications and advancements in the fields of IIoT and Industry 4.0 are reviewed. Sensors and their use in new and old systems, security considerations around such systems, potential challenges with IIoT and Industry 4.0, and recent IIoT and Industry 4.0 installations in industrial facilities are mostly covered.

The survey in [16] provides an in-depth discussion on a variety of topics connected to the Internet of Things, including architecture, supporting technologies, issues, and applications. Furthermore, the study organizes the link between Industry 4.0 and IIoT and proposes an IIoT architecture based on this relationship: data, application, security, and services. Furthermore, this survey contributes to the literature by examining how IoT might aid in the resolving of healthcare issues.

The authors of the article in [17] concentrate on the two enabling technologies for IIoT: edge and fog computing paradigms. They take a use-case approach to show how edge and fog computing are positioned to make a difference in various industrial applications. They also highlighted current concerns and challenges these paradigms confront in the IIoT and potential research directions.

A survey on the usage of federated learning for IIoT applications has been proposed in [18]. At the beginning of the study, various motivations for integrating federated learning with IIoT are presented. Also, their discussion stated that federated learning is an effective approach for protecting user data by training the model without transferring the data from the client to the main server. Furthermore, the security mechanism's scope can be expanded by sharing model updates and combining data provided by similar devices from various industries. In addition, the survey covers two crucial topics: blockchain and data management in IIoT using federated learning. Finally, the survey identified possible applications and technical hurdles in developing and delivering real-time applications.

The authors of [19] proposes an examination of historical and current IIoT design and a detailed comparison of various state-of-the-art continuing standardized interoperability processes. First, the survey provides an overview of different IIoT paradigms and important Industry 4.0 objectives for the interoperable industrial revolution and examination and revision of various interoperable patterns and difficulties linked to IoT, IIoT, and Industry 4.0. Then, for future IIoT ecosystems, research will focus on various newly established interoperable supported protocols and standards. Finally, the study adds to the literature by highlighting several major challenges, prospective solutions, and future possibilities for dealing with different interoperability concerns.

However, and based on the detailed investigation of the related work presented above, our survey address certain key problems, including:

1) Most related work lacks a detailed explanation of IIoT challenges and difficulties and how these challenges have been addressed and managed.
2) Furthermore, most related articles failed in narrowing the gap between Industry 4.0 requirements and enabling technology.
3) Discussed related works have significant limits in terms of providing possible IIoT developments and a lack of discussion on future IIoT architecture.

The survey contributions can be framed as follows, based on the gaps mentioned above:

1) Based on an analysis of a wide range of articles from the literature, we provide a novel taxonomy of IIoT challenges. The literature review leads to a discussion of the main aspects of each challenge, such as the terminology and approaches utilized to solve these challenges.
2) The study provides comprehensive discussion about Industry 4.0 in terms of concepts, requirements, and supporting technology. In addition, we discuss the correlation between enabling technology and technical requirements in detail.
3) We propose a new architecture for the future of IIoT based on three primary techniques: deep learning, edge computing, and big data. The presented technique is thoroughly examined to present a different method for future adoption.

The rest of the survey is organized as follows. In the section II, Industry 4.0 in terms of requirements and technologies are illustrated. Section III presents an overview of IIoT terminology and architecture beside use cases related to IIoT. IIoT challenges are discussed in the section IV. The section V explains the potential techniques for IIoT and their usage. Finally, we conclude the survey with a conclusion.

C. SURVEY LIMITATIONS

The study's findings have to be seen in the light of some limitations as with most studies. Limitations in this survey are explained in the following points:

1) In order to make a more practical contribution, it is necessary to have a modern and adequate quantity of prior works. On the other hand, our study aims to fill in the gaps by applying in-depth analysis to the information gathered from the literature.
2) Despite the endeavor to offer a thorough overview by covering several techniques and technologies that have been used in various ways to handle IIoT challenges, this study misses some approaches that have been conducted in this context.
3) This study focuses on discussing the majority of Industry 4.0 enabling technologies to clarify various elements and methods for using them in particular; nevertheless, future work should address the design perspective for Industry 4.0 and the technologies and applications.
4) This survey skips the brief discussion of the security aspects of IIoT mainly because of the massive amount of work in this context.
5) Because the research focuses on the technical characteristics of Industry 4.0 and IIoT, human-based requirements for Industry 4.0 are shortly described.

II. INDUSTRY 4.0 OVERVIEW

Industry 4.0 is a term that has been discussed in the last ten years; initially, it refers to the integration between many emerging technologies with manufacturing [20]. Industry 4.0 can be considered as the new generation of industrial environments; it aims to reduce human intervention and efforts and replace them with an intelligent environment. The starting point of the initialization and building Industry 4.0 environment is merely transforming the manufacturers that depend on the traditional machine to digital manufacturing [1]. Digital transformation results in a systematic integration of smart machines, computers, smart devices, and methods of communication; this integration allows for real-time decisions with minimal involvement of human activities.

Industry 4.0 has several advantages that enforce and push the aforementioned transformations, such as efficient resource management, enhanced productivity, and improved safety and security. Industry 4.0 is a better reflection of continuous technological and production growth over the decades. The first generation of manufacturing was stratum until the end of the century about 1850; human and mechanical machines performed all the work. The second-generation initialized about 1870 until 1970 when the production was assisted by electricity. By the beginning of 1970, the third generation leveraged the assistance provided by computer systems [1]. In 2011, Germany introduced new partnerships among many associations. They called it ''industry 4.0,'' which focuses on delivering machine autonomy and self-behavior by enhancing the process of transforming digitalization to involve many technologies [21]. In this context, the German project was the seed of later projects.

Similar to what has been suggested in [22], Industry 4.0 could be made up of at least four components or levels that work together to create a certain industrial application. The device, control, production, and enterprise levels are the four industrial levels. The first level, which connects with the production process via sensors and actuators, is the device level. Both machines and systems are regulated at the control level. At the same time, order management and processing and larger overall production planning are managed at the enterprise level.

IIoT, and Industry 4.0 are two different ideas frequently used interchangeably. While Industry 4.0 refers to the necessity of lean, efficient operations and the function of sustaining and improving production, IIoT, on the other hand, separates manufacturing equipment from consumer products that wirelessly link to internal networks and the internet. The main points where Industry 4.0 and IIoT differ are:

1) Industry 4.0 focuses primarily on manufacturing, whereas IIoT covers all sectors where industrial/professional equipment is used.
2) Industry 4.0 covers the pure connection of assets and data management and the digitization of the complete value chain.
3) Industry 4.0 is more closely associated with governmental and institutional initiatives and only gaining traction in a professional setting.

Designing Industry 4.0, subject to several considerations: First, knowing the process at the factory level is required to evaluate the type of company behind the manufacturing process. The second stage involves managing the product's manufacture and satisfying consumer requirements. As with the lifecycle, these four aspects need to be examined, and optimized [1].

Technically, Industry 4.0 is a mix of multiple innovations and systems such as IoT, Big Data, Artificial Intelligence, and many others, which function together to satisfy the application requirements. However, other aspects are deeply influenced by several numbers of strategies that are involved and how they interconnect with each other, such as the environment, quality of output expected, and expense [2].

It is mistaken to limit the use of Industry 4.0 to the manufacturing scope only because it crosses the borders to be conducted in many other areas. In [23], the article discusses the role of Industry 4.0 in education. Authors in [24] discuss the impact of Industry 4.0 and beyond on biotechnology.

Smart home is another scope that is discussed widely under Industry 4.0 as provided in [25].

A. INDUSTRY 4.0 REQUIREMENTS

Any new technology needs specific requirements that must be partially or wholly satisfied. Industry 4.0 has many assumptions or parameters that need to be at least partly enforced. Any proposed project or structure could be inspected according to these requirements; this inspection may indicate the consistency and robustness of the proposed project. In [26] and [1], several requirements for Industry 4.0 has been provided. Accordingly, this survey perspective can be divided into two types in terms of Industry 4.0 requirements: the human-based requirements and the technical-based requirements.

Human-based requirements provide the criteria for training human workers to play their duties in the Industry 4.0 environments. These requirements begin with training, then assign the tasks, and finally monitor the human-machine interconnection to optimize the overall production or manufacturing processes. However, and according to [27], [28] and [29] there is still a lack of research that outline the overall human requirements, especially with those related to ethics.

Technical-based requirements contain the requirements related to computing aspects in the production or manufacturing phases. these requirements are :

1) Autonomy: Mean the system's capacity to practice self-behavior or make decisions, as well as to minimize human involvement [1].
2) Real-Time Processing: The device has to capture and interpret the data and function correctly with a slight delay in real-time.
3) Data Analysis: Massive data were generated by the industrial system, some of which were related to the production and manufacturing, while others were related to the system status. Data processing will have a significant effect in two directions: First, the data analysis can maximize the output of the overall program. Analysis of status data in the second direction can help the system to adapt to any emerging changes and predict errors prior to their occurrence [1].
4) Interoperability: To optimize the experience, data generated during the product lifecycle from the manufacturing to the end customer must be shared. This lifecycle involves various data formats, protocols, and vendors. The interoperability provides the entire system with the required management into different stages of data processing.
5) Efficient management of resources: Number of elements in industrial systems has increased rapidly, so there is a critical need to provide a resource management mechanism to reduce the expected complexity.
6) Modularity: Modular systems can be easily adapted to changes or differences in product characteristics or to replace any component due to any damage.
7) Organization standardization: Define standard architectures, protocols, and mechanisms to support system component collaboration. This issue is essential to overcome the heterogeneity challenges caused by multiple technologies, where each technology has its complexity and pipeline processing.
8) Security: The industrial system contains multiple data movements between different components of the system; these data must be secured inside the physical part itself and secure the paths between elements.

In the perspective of Industry 4.0 architecture, Figure 1 displays the Industry 4.0 technical requirements. Autonomy, interoperability, organization standardization, resource management, and security are all related to the supplied architectural structure levels in the figure. These requirements must be taken into account and maintained throughout the development process. On the other hand, modularity is linked to the device, control, and production levels. Data analysis is necessary at the control and product levels, whereas real-time processing is only required at the control level.

B. INDUSTRY 4.0 ENABLING TECHNOLOGIES

Industry 4.0 has many heterogeneous standards or frameworks [1]; this fact allows Industry 4.0 frameworks to be constructed in a heterogeneous way. As a consequence of this complexity, a new structure that adopts various technologies will arise. Industry 4.0 is based on cooperation among several technologies and can be regarded as enabling Industry 4.0 technologies.

several supporting innovations can be used to meet the criteria of Industry 4.0. Implementing these technologies varies from one industrial field to another; certain industries rely on the general product level. Thus they follow the idea of the Cyber-physical system (CPS), which is also called the cyber-physical production system (CPPS) [20]. Other environments are trying to narrow the range of technologies, such as those that integrate the Internet of Things (IoT); these systems are called the Industrial Internet of Things (IIoT) [10].

The major enabling technologies for Industry 4.0 are listed in the following points; however, the overall technologies are not limited to these:

1) Cyber-physical system (CPS): CPS concept consists of three primary components: physical devices, communication networks, and control systems. CPS currently encompasses the Internet of Things (IoT), Smart Vehicle Network, and several other [30] technologies. CPS should fulfill many criteria for delivering a smart production system to support Industry 4.0. In the literature, several researchers are seeking to explore ways to combine CPS with Industry 4.0, including the study in [20].
2) Internet of Things (IoT): IoT uses sensors and networking technologies to detect and relay data in real-time. The IoT allows for quick calculations and optimum

TABLE 2. Relationship between industry 4.0 requirements and enabling technologies.

Requirement / Technology	CPS	IoT	M2M	Cloud Computing	Big Data	AI	Digital Twin	AR	Blockchain
Autonomy	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Real-Time Processing	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Security	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
Resource Management	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Interoperability	Yes	Yes	No	Yes	No	Yes	No	No	No
Organization Standardization	Yes	Yes	No	No	No	No	No	No	No
Data Analysis	Yes	Yes	No	Yes	Yes	Yes	No	No	No
Modularity	Yes	Yes	Yes	No	No	No	No	No	No

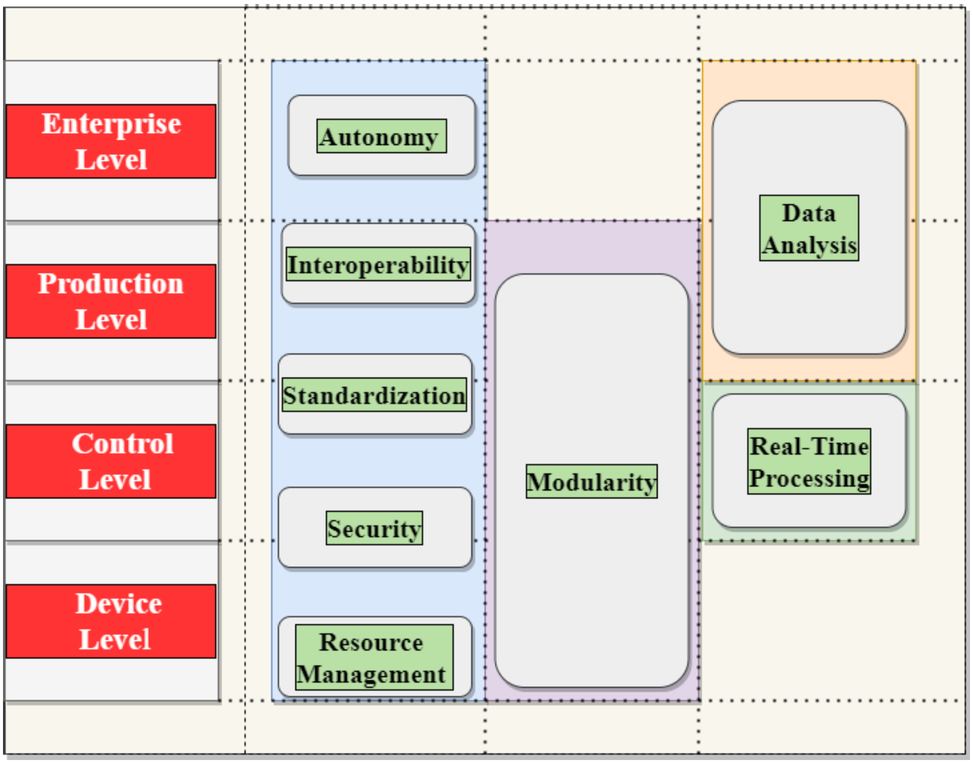

FIGURE 1. Industry 4.0 technical requirements.

decision-making. IoT is growing tremendously, and its influence is spreading to create innovative futures through urban communities. However, IoT technologies are focused on allowing users to be in a more comfortable environment. IoT integration with Industry 4.0 enables sensor connectivity capabilities and facilities to be used to enhance industrial production processes [10].

3) Machine-to-Machine Communication (M2M): M2M is a fully automatic inter-device communication without human intervention [31]. M2M is a technology that enables businesses to develop wireless connectivity, particularly between information centers and machines. Until M2M, the connection was made by allowing a remote machine network to transfer information back to a central analytical node, which will then be routed to a device such as a personal computer.

4) Cloud Computing: Cloud computing delivers on-demand computer resources from applications to storage and processing facilities, typically remotely and at cost. Applying cloud computing systems should be sufficient for Industry 4.0 to raise resource demand. Cloud infrastructure is the most open computing facility, enabling ease of operation of computer processing. The essential feature of cloud-based data is its robustness and reliability. It also allows for a virtualization framework that offers real-time, reliable, value-added, and usable manufacturing data for optimum configuration and organization of large-scale production [1].

5) Big Data and Data Analytics: Technically, big data are organized /unorganized raw data with a large volume. The big data function depends on a specific processing mechanism to extract meaningful value from big data, leading to analytical data. Given the enormous amount

of business data produced, optimal computing capacity, computational capability, and knowledge technology expertise are required. The most popular way of implementing big data features is by performing data processing in the manufacturing system or Industry 4.0 environment rather than transferring it to another external party to perform the analytical steps and then forward back the result to the industry environment [10]. This data collection will accomplish many of the most critical objectives, including increasing energy performance.

6) Artificial Intelligence (AI): AI is the ability of a computer-controlled device or program to execute tasks typically associated with human beings. It contains numerous branches such as machine learning, robotics, optimization, algorithms of evolution, and many others. Regrading Industry 4.0, two divisions arise as the critical divisions, the first being machine learning (ML) and the second being robotics. ML to provide self-decision systems and automation problem solutions, while robotics can be used to promote efficient digital development through reduced effort and human interaction [1].
7) Digital-Twins: A digital twin is a virtual model that parallels and processes a physical product during its lifespan. They offer an almost real-time bridge between the physical and digital worlds. The digital twin digitally develops virtual models for physical objects to simulate their behavior. Digital models may recognize the physical entities' condition by sensing data to expect, approximate, and evaluate dynamic changes. Simultaneously, the physical objects react to the changes by simulation according to the configured scheme. Virtual twins can achieve optimization of the entire manufacturing cycle via a cyber-physical closed loop.
8) Augmented Reality (AR): AR includes a series of technologies that use an electronic system to display, explicitly or indirectly, a real-world virtual environment coupled with virtual elements. Concerning Industry 4.0, AR allows employees to communicate virtually, connect with real-time information, and track and control systems. AR can also assist staff in controlling activities by providing written, visual, or auditory input guidance. Another area in which AR can help Industry 4.0 is by delivering the correct details at the right moment to prevent mistakes and improve efficiency [32].
9) Blockchain: A blockchain is essentially a database or ledger with important features such as shared, distributed, decentralized, recording assets and transaction details using a peer-to-peer (P2P) network. The decentralized feature of blockchain is particularly important for Industry 4.0 to improve and speed up communication between system components. Blockchain also guarantees trust in the data in real-time. Another important aspect of the blockchain is the existence of a smart contract that provides a method of trust executions over a network workflow [33], [10].

Table 2 shows the relationship between Industry 4.0 requirements and enabling technologies. The relationship in this perspective means that each technology can satisfy a given requirement. CPS, for example, is a comprehensive terminology that can lead to meeting all Industry 4.0 needs because of collaboration between its three components. IoT can be considered as a bedrock for Industry 4.0 because of the computing facilities and adopting flexibility. M2M is an important technique for achieving certain requirements, especially autonomy and decision making. Because of the many features are given as a service, cloud computing involves many aspects such as data analysis and resource management? Big data is a fundamental technique for any system that requires data processing and analysis and can contribute from this perspective. AI has a wide range of methods and techniques and can provide Industry 4.0 with many features that fulfill the requirements needed, such as support decision-making and automation in real-time. AR and digital twin are trends technologies that expect to have a respect level of impact in many Industry 4.0 requirements, especially modularity and autonomy. Finally, blockchain shows promised vision in terms of security because of multiple data security and privacy features.

III. INDUSTRIAL INTERNET OF THINGS (IIoT)

The industrial Internet of Things (IIoT) is a technological evolution that enhances the industry's manufacturing and economic impact. The technical development mentioned results from the IoT feature, such as sensing, actuating, interconnecting, and the ability to process the data at different levels. IoT technologies bring many capabilities and benefits to manufacturing environments, including data acquisition, data processing, and finally, smart decision-making with limited human intervention.

Internet of Things (IoT) allows consumers to profit from the ubiquitous digital revolution. In contrast, the Industrial Internet of Things (IIoT) provides machine-to-machine (M2M) communication, which helps industries across industries. The Industrial Internet of Things is being shaped by digitization, wireless networking, and automated sensors, directing the operational and production processes (IIoT) [10].

During the previous decade, hardware, remote access, big data analytics, cloud, and machine-learning improvements have bolstered industrial automation [34]. As a result, an organization may pursue internal, external, and communal advantages. Those who are unfamiliar with IoT and IIoT sometimes confuse the two acronyms. On the contrary, they are two similar technologies that use the same standard protocols, which means that their concepts are frequently copied from one another [35]. They may have the same user interface, intelligence, and agility. However, their operational procedures, philosophies, users, and goals are distinct [13].

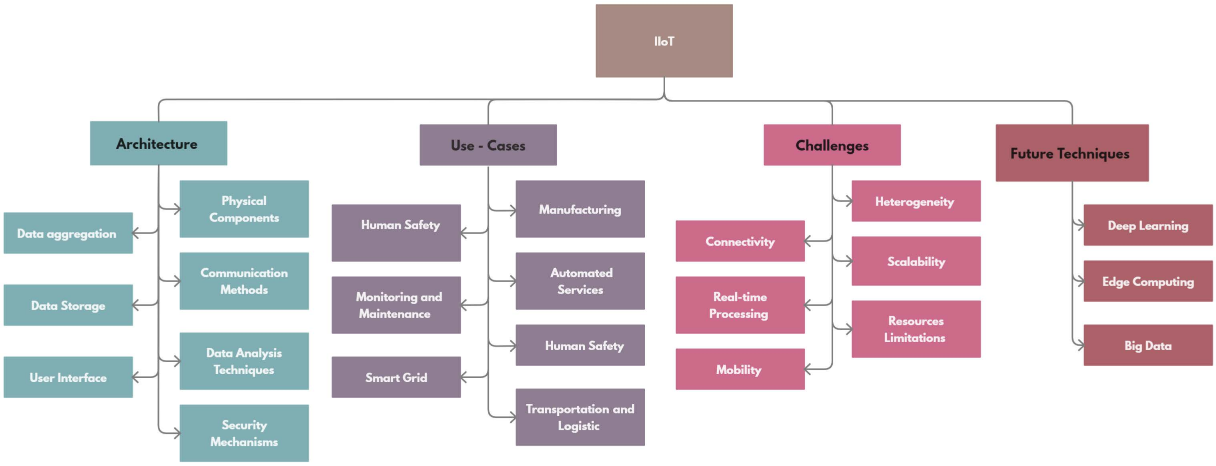

FIGURE 2. IIoT topics illustration.

In terms of application, IoT aids in the optimization of consumption, enhancement of personal comfort, and cost control. In contrast, IIoT strives for maximum efficiency and seamless workflow in any processor unit [10]. In terms of use cases, IoT is used to automate day-to-day home procedures, whereas IIoT is mostly used to monitor production and environmental aspects in businesses. IoT solutions require programmable learning capabilities in system architecture to connect control and automation logic in the gateway with new production execution systems, which is an important distinction [10]. The IIoT architecture is designed to meet low latency requirements while dealing with errors or malfunctions, and it should automatically re-route to the backup system [36]. In addition, IoT-enabled industrial equipment must withstand extremes in temperature, volume pressure, harmonic vibrations, and other factors at a distance. They should sustain severe duty cycles while remaining within tolerance and operating for decades [37]. Finally, scalability is an evident characteristic that distinguishes IIoT from IoT. Thousands of new sensors and non-IoT devices are installed in an IIoT network comprising controllers, robotics, machines, and other utility-derived applications in an enterprise. Scheduling, data collecting, analysis, interoperability, workflow integration, decision-making, and interaction with industrial and business-oriented systems may be scaled with such a network [10]. Table 3 shows the differences between IoT and IIoT.

A. IIoT OBJECTIVES

Despite the essential role of IIoT in Industry 4.0, until now, there has been no general architecture for this integration. In this study, we seek to tie all the possible objectives behind this integration to consider the major benefits of this integration:

1) Production Enhancement: IIoT can enhance the transition to automation in Industry 4.0; this is a powerful matter in reducing human intervention. Minimizing human interference and manual labor will lower the cost of production and increase efficiency.
2) Efficient data processing: IIoT has many advances in Big Data processing and machine learning algorithms [38], which can optimize data processing and, in particular, real-time data. IIoT comes with many solutions that facilitate the application of data analytics methods [39], and data analytics can undoubtedly lead to self-decision support. IIoT usually utilizes the cloud for data storage; the relationship between IIoT and cloud can provide many features for industrial enterprises such as visualization, data logging, user-friendly interfaces, and remote access for data.
3) Generalization: IIoT provides many common characteristics, such as data collection processes, network protocols, and physical devices. IIoT standards may bring some generalization to any forum or initiative within the industry. These standards can reduce by Industry 4.0 challenges in some industrial sectors, such as scalability and heterogeneity [40].
4) Monitoring and Maintenance: The sensing capabilities provided by IIoT allow industrial safety procedures and alarming methods to be established. Safety procedures can be enforced by monitoring and predicting the industrial environment and errors before they occur. On the other hand, limiting human interference would lead to minor human mistakes, eliminating regular maintenance.

Figure 2 shows the roadmap for the rest of this survey. This survey will discuss some important topics about IIoT, including suggested architecture, common use cases, a new taxonomy of challenges, and techniques for future deployment.

B. IIoT ARCHITECTURE

This survey idea of the IIoT architecture is built on the collaboration of numerous components or levels. Figure 3 depicts

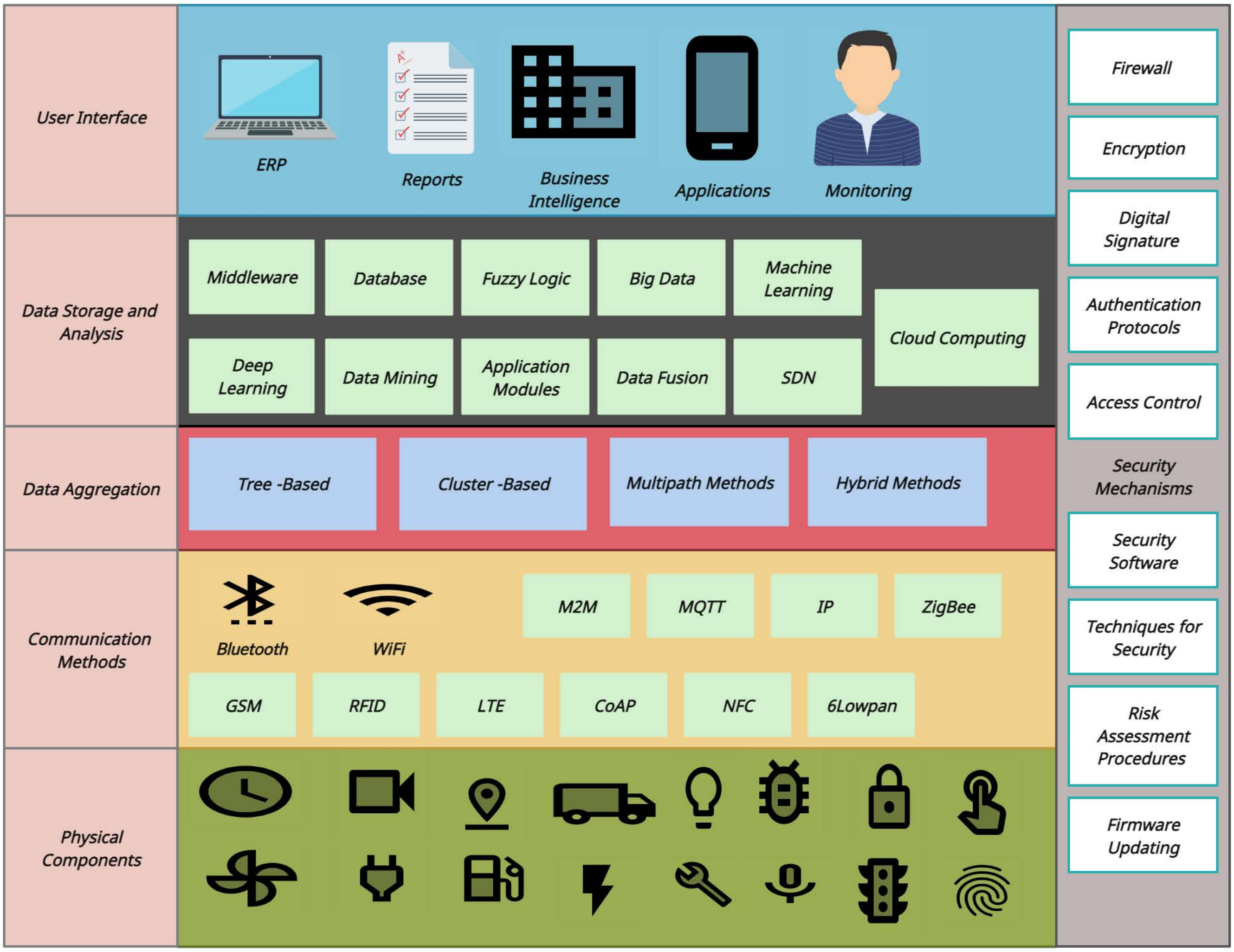

FIGURE 3. IIoT architecture.

the architecture proposed by the survey. At least, the existence of these components is required if the objectives of IIoT integration are to be met. Those components are:

1) Physical components: contains all physical objects in the manufacturing system. The most important items are machines that perform the industrial production work. Other objects are sensors, actuators, and gateways; as explained above, they bring other characteristics to the industrial framework.
2) Communication Methods: IIoT is heavily dependent on the wireless protocol for transferring data between network elements, such as (6LowPAN) [41]. Communication methods in IIoT need to fulfill various specifications, including low power consumption, high communication capacity, and stable interconnection. Nevertheless, these specifications may vary from sector to sector; for example, M2M connectivity involves a high-reliability link as the highest priority, while high-bandwidth connectivity from computer to cloud is the highest priority.
3) Data aggregation methods: Data aggregation is a mechanism in which multi-data packets are obtained, and one output packet is generated. Considering the overwhelming amount of data produced from physical objects, data aggregation is an important feature of IIoT. By eliminating the existing complexity, aggregation may provide a consistent description of such data. There are currently four primary data aggregations: centralized, in-network, tree-based, and cluster-based techniques [42].
4) Data Storage: Cloud currently used by IIoT for data storage. The cloud as a platform has robust software and hardware in nature. As storage, the most crucial feature of a cloud is its scalability. Data stored in the cloud can be analyzed or interpreted quickly using AI or data-mining algorithms. Recently, different layers of clouds, such as fog computing, may improve the latency. In addition to the cloud, specific manufacturing networks may use individual data centers or servers to store their data according to their plans and strategies.

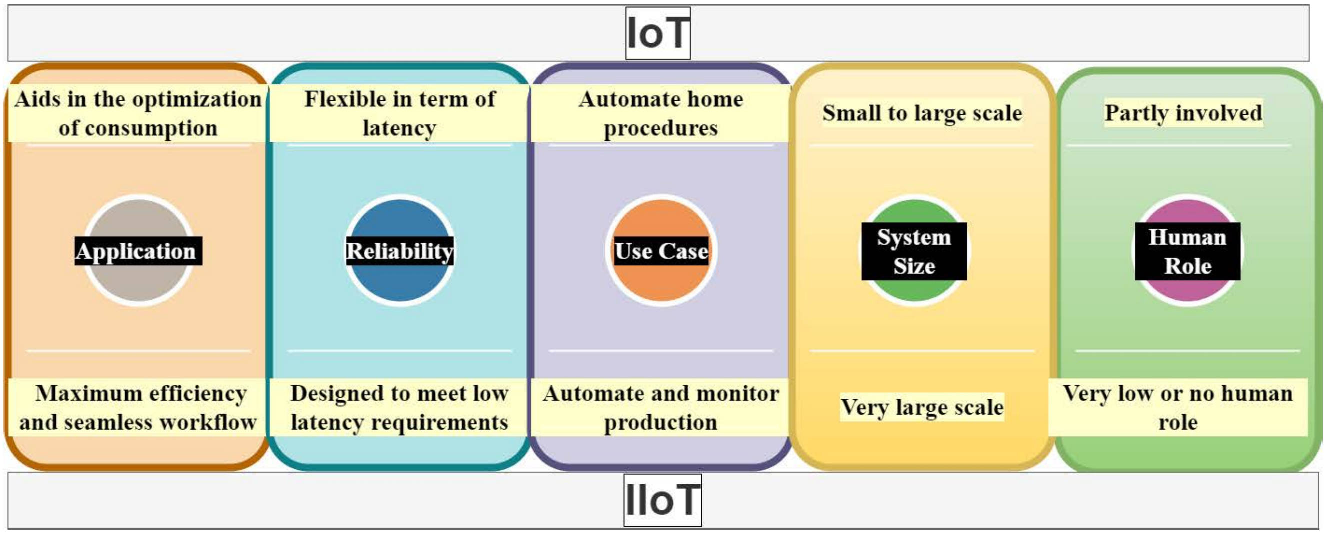

FIGURE 4. IoT vs IIoT.

TABLE 3. Differences between IoT and IIoT.

Perspective	IoT	IIoT
System size	Small -to - medium	Medium-to-large
Usage	Optimize consumption	Maximum efficiency
Use Cases	Personal use	Productions and business
Reliability	Flexible	Low latency
Automation	Limited	No human intervention

5) Data Analysis Techniques: Optimizing the performance of the manufacturing network or IIoT network over time is vital; this can achieve this by applying statistical methods, data mining, Big Data techniques, and machine learning algorithms that implement most analytic data techniques. Data analytics enriches the IIoT with other features such as reduced resource consumption, quality of service (QoS), automated support, failure detection, and maintenance optimization. Data analytics is typically developed for the data collected in the cloud because the cloud has many resources that automate the collection and analysis cycle.
6) User Interface: Typically, there is a system control interface on the application layer, and IIoT can support user-friendly applications with its level of data standardization and protocols. Interfaces must be operable for different applications and hardware. Using these user interfaces, IIoT improves industrial networks with the remote-control functionality of the system.
7) Security Mechanisms: Security and privacy are the most critical aspects that must be addressed when designing any manufacturing system. Typically, these elements are implemented using specific methods such as protocols, encryption techniques, permissions, firewalls, and many others. Some manufacturing systems exploit other technologies, including security and privacy features, such as machine learning and blockchain.

C. IIoT USE-CASES

1) MANUFACTURING

Manufacturing is the process of making a product; this process typically involves multi-level processing — IIoT seeks to bring more innovations to manufacturing and implement a smart factory. Smart devices, electronics, and communication methods can boost production processes in a smart environment. This enhancement mainly affects manufacturing speed and flexibility, which means producing completely flexible production at the highest pace, especially when there is an extensive transition from conventional methods to advanced technologies. Smart factories often have to do with fascinating technological methodologies such as augmented reality, simulations, and virtual prototypes [43]. In [44]], the authors highlighted the requirements and essential concepts associated with the smart factory, including sustainability and predictive engineering.

In [5], the authors built a general, intelligent factory architecture and explored the operating structure that organizes the involved technical components. Many criteria and challenges in designing a smart factory system have been explored in this work, including a multi-aspect comparison between conventional factories and smart factories.

2) AUTOMATED SERVICES

Automation is the concept of performing a job with minimal human interference [1]. IIoT can effectively support autonomy based on sensed data, depending on the decision-making process. The IIoT lifecycle began with data sensing, and then the data were transferred to the storage. One can apply data analysis in the automation context at this point, which induces intelligent decisions. IIoT, with the above mechanism, can be used to automate many services with a high level of dynamicity.

The authors in [45] proposed what they call the pyramid of automation in the context of IIoT. This pyramid was made of multiple levels. A first-level ''field level'' where there are physical devices. The second level is the level of control, and its role is to make an intelligent decision. The third level is the supervisory level, which is responsible for the centralized control of multiple remote locations. The fourth level is a planning level that manages and tracks the overall system processes. The final level is called the management level, which implements the highest degree of automation that incorporates the monitoring and control of all activities, such as manufacturing processes and details of human resources. In [46], the concept proposed by the authors is a solution based on Industry 4.0 for the milling process regulation. IIoT uses instruments, machines, and processes to interconnect in this system. The result controlled the manufacturing process, which can predict various product characteristics and automatically adjust to give the product the desired quality level.

3) HUMAN SAFETY

Human safety in every organization is a major concern, particularly in industrial organizations where employees operate in high-risk locations. IIoT can help provide and identify several things that can guarantee employees' health.

The idea of a connected workforce is an example of how IIoT is used to show how workplace safety and workplace well-being are strengthened and healthy work practices are required. Such a framework tracks the biometrics of a worker, the level of exposure to nearby hazards, and relays the information to nearby workers [6]. Establishing IIoT-based safety systems will improve the overall efficiency of industrial organizations by implementing successful human resource management and reducing workplace accidents. In [47],Authors propose a safety-as-a-service (Safe-aaS) platform that provides end-users with personalized security-related decisions. Safe-aaS end-users are on-site working staff, officers, and numerous government departments. The decisions made by the system consider t multiple factors, s such as machine downtime, machine performance, and worker safety.

4) MONITORING AND MAINTENANCE

Monitoring is an important characteristic of a manufacturing system; monitoring is typically constantly applied to maintain high-quality output performance. IIoT can reduce manual monitoring, sensors, and other IIoT elements that provide high versatility in monitoring.

IIoT will respond to any emerging behavior or anomalies and make the right decisions. Monitoring may also help maintenance; IIoT may provide predictive maintenance, which is the process of predicting possible system failures and scheduling necessary maintenance prior to the breakdown [6]. In [48], the article suggests IIoT architecture links innovative sensing systems to manufacturing ecosystems through big data analytics. The proposed approach is validated in a real-life case study, a large industrial organization that offers a solution for temperature monitoring of electrical substations. The proposed architecture analyzes the layout and settings needed for autonomous and intelligent sensing devices to provide reliable temperature measurements with minimal intervention and robust detection of faults.

5) SMART GRID

A smart grid allows for bidirectional transmission of electrical energy and coordination between suppliers of electrical power and consumers [49]. Across several ways, IIoT will automate smart grid functions, beginning with reduced fossil fuel usage, increased use of renewable energy resources, and improved electricity use. It is also expected that IIoT-based energy technology can automatically solve the problems of inaccessible independent renewable energy sources by tracking energy usage, energy production, and collaboration with other sources. In [50], the authors suggested a framework to allow IIoT technologies and handle real-time data energy models by setting flexible routes for grid control commands in a smart grid scenario. This framework aims to minimize the traffic load at the center of the network and end-to-end latency between smart utility systems.

6) TRANSPORTATION AND LOGISTIC

Logistics is a strong component of modern industrial enterprises. When using conventional methods, controlling goods in storage and transportation is a strict procedure. From several aspects, the IIoT will boost logistics.

Some of the essential elements of large manufacturing environments are controlling the condition under which particular items are stored and ensuring that they are appropriate for the products. Establishing IIoT with robotics will provide a high return on investment to the industry organization, increase efficiency, improve the quality of the process, and contribute to a more effective and safer workplace [6].In [37], the architecture for smart production logistics systems designed to enforce smart modeling of fundamental manufacturing properties and investigate self-organizing configuration processes is proposed. A data-driven architecture was built to incorporate a self-organizing structure based on empirical target cascading.

IV. IIoT CHALLENGES

Implementing IIoT in the industrial sector faces many challenges; these challenges occur primarily owing to the IoT characteristics. Depending on the relationship between IIoT and IoT, the IIoT problems are not fundamentally different from those applied to the IoT. The most well-known IoT characteristics are limited to memory capacity, low energy consumption, wireless connectivity, and restricted processing capabilities.

Next, the survey reviews each challenge in terms of IoT and presents the suggested solutions in the literature with a brief description.Additionally, this survey proposes a detailed analysis of the strategies used to address current IoT challenges in

Figure 5, which will offer a detailed vision of the technique's utilization in various ways.

A. HETEROGENEITY

IoT heterogeneity involves the application of various communication protocols, data formats, and technologies [10]. IoT is being used in almost every sector and different functional areas and is expected to be adopted in a huge range of diverse applications. The aforementioned IoT systems use a diverse set of protocols, distinct patterns of architecture and design, and diverse specifications. These devices are heterogeneous to one another in a way. In data terms, IoT data are written in various formats, such as RDF, microdata, and microformats. IoT networks use different techniques and protocols. Additionally, IoT devices are manufactured according to the requirements of various vendors. Interoperability is one of the key solutions to the heterogeneity problem; IoT interoperability can interconnect and communicate different vendors' systems, data formats, and protocols to build the infrastructure needed.

Semantic interoperability-based architecture was adopted in [51]; which aims to offer an obvious definition for exchanging information. It integrates semantics in the data by adding packages of self-described knowledge. Semantic operability is used to ensure the interoperability of IoT devices from various vendors. To make it meaningful with a common vocabulary, IoT devices take data from the user interface portion of the system and then add semantic annotations. The technique for data analytics is applied to data obtained from IoT devices to undergo syntactic and semantic modifications to make it more cost-effective and useful.

Within the same sense of semantic approaches, the approach [52] proposes a mechanism for using social users' collective wisdom and incorporates semantic fusion crowdsourcing g computation in the sense of Internet of Things (IoT)-based environments. The process began by collecting semantic knowledge from crowdsourcing participants. Semantic objects are then converted to a single format, and the number of dimensions is minimized such that redundant details are removed. The information generated from the previous steps is stored in a database that provides consistency and is distributed with the media files.

Data unifying is another solution to the data heterogeneity. In [53]the author proposed the Internet of Things as a platform for data sharing between heterogeneous data sources. This framework aims to unify raw data sources and make them freely accessible and allow users to share their service edge and have additional data collection features and personal computing features. To test the framework, the data considered were open data accessible by public clouds such as Thing Speak and Spark Fun. A specific middleware performs the mechanism of data unifying.

Another approach to data heterogeneity is identifying and retrieving such IoT data attributes. The solution in [54] proposed a system for data storage and retrieval by analyzing and retrieving common features of IoT data produced from different sensing devices. The system process of work starts with the acquisition of heterogeneous IoT data. The data are then stored, and after inserting the data into a standard database, the URL and data type will be generated. Next, the entire data record is processed in the Database of Key-Value (Redis). The serialization method is defined using a specific ID assigned to classify the record. This system then stores the ID and the associated index relationship in Redis and the column-oriented database (HBase) according to the time attribute and frequency of access, respectively. Owing to its resident memory, Redis is used to store real-time and high-frequency data. As a database focused on HDFS, HBase was used to store low-volume historical data.

The description methods of IoT devices are another way to solve the heterogeneity problem, where devices and services are described in unified ways that allow resource sharing. The solution constructs an ontology-based resource description model of IoT devices in [55] to provide a coherent view of heterogeneous sensing systems in the cloud for IoT applications. The architecture is expected to operate on the network's edge between the cloud IoT infrastructure and heterogeneous terminal devices. Access control was built within the architecture. The access strategy facilitates hierarchical downward connectivity to heterogeneous terminals and offers a single upward software interface for top IoT applications. Model includes the sharing of IoT devices and services as a function of the operating process.

AI and learning concepts implement a practical approach to handle heterogeneity in IoT. In this context of learning methods for heterogeneity. Work in [9] provides a good background for the use of IoT learning strategies. The authors explore the different learning frameworks appropriate for solving many of the IoT's important issues, such as machine learning and sequential learning. Then, they summarize the core principles, major problems, possible implementations, and real outcomes for each learning method. Eventually, the study proposes using cognitive hierarchy theory as a promising technique to effectively model the IoT to address the shortcomings in learning strategies, as it offers a modeling context that can adequately capture the heterogeneity among the agents.

Table 4 provides a summary of the above solutions.

B. CONNECTIVITY

Increasing demands on many performance aspects, such as energy consumption, decreased latency, better response time, and scalability, are part of the IoT future. IoT applications are time-sensitive and require streaming instead of batch processing in real-time [65], [119]. The throughput, network speed, data rate, and computing space can be estimated based on the amount of data used and where it is stored. Latency is the sum of delays in transmission, processing, propagation, and queuing for a network. There is a need to mitigate all types of delays to meet the low-latency specification [119].

Cloud computing has been embraced as an evolving option for challenging IoT requirements to manage large volumes

TABLE 4. Heterogeneity solutions summary.

Reference	Specific Issue	Solution Name	Solution Summary	Involved Techniques	Implementation
[51]	Multiple Data Formats	IoT-SIM	Model consists of semantic interoperability and the cloud, which semantically annotate patient data and convert it to RDF and SPARQL queries, which can be used to extract data from any patient at any time	Big Data Cloud Computing	Yes
[52]	Semantic Fusion	Crowdsourcing Semantic Fusion	Semantic model processes semantic information taken from crowdsourcing users and normalizes it to a single format to mine knowledge	Big Data Data Fusion	Yes
[53]	Data and Communication Heterogeneity	None	Architecture capable of integrating data from many sources and processing processed data can be collected and used by various services	Big Data	No
[54]	Data Retrieval	HSFRH-IOT	System that analyzes and extracts common properties of IoT data before storing them in two distinct databases solves the challenge of receiving, storing, and quickly retrieving huge amounts of data	Big Data	Yes
[55]	Resource Access	Smart City Road Manhole Cover Monitoring System	IoT access platform architecture relies on edge computing to tackle the resource sharing problem of IoT's vertical application mode and the unified access problem of heterogeneous terminals	Edge Computing Resource Description	Yes
[9]	Seamless IoT Deployment	None	Define cognitive hierarchy theory and its application to IoT technology in order to identify the main linkages between cognitive hierarchy theory and the various kinds of deep learning algorithms	Machine Learning	Yes

TABLE 5. Connectivity solutions summary.

Reference	Specific Issue	Solution Name	Solution Summary	Involved Techniques	Implementation
[56]	Latency Issues	IFCIoT	Fog node design with multiple layers monitors application attributes and reconfigures architectural resources to meet peak workload	Cloud Computing Fog Computing	No
[57]	QoS Provision	QoS-Fog	Five-level system hierarchy for managing smart services QoS to improve performance ,latency, energy consumption, and network utilization	Fog Computing	Yes
[58]	Resource Allocation	AHP	Self-organization as fog and analytic hierarchy for dispersed user association and resource allocation for mapping network resources to IoT applications.	Fog Computing	Yes
[59]	Latency Issues	None	Matching theory-based approach in which an IoT node may be matched to a single cloudlet and a cloudlet can have many IoT nodes, in addition to appropriately associating users for maximum joint utility.	Edge Computing	Yes
[60]	Resource Allocation	None	A decentralized software-defined storage system addresses mini clouds storage capacity constraints and decreases access latency.	Software Defined Storage Cloud Computing	Yes
[61]	Resource Allocation	None	Service-oriented resource management approach for IoT devices using fog which can aid in resource management	Fog Computing	Yes
[62]	Latency Issue	None	A three-tier approach with intermediate fog and cloud data centers to adjust packet pathways resulted in lower latency and more autonomous processing.	Fog Computing 5G	Yes
[63]	Resource Allocation	IoT-Gateway	5G-enabled IoT gateways that offer uplink IoT traffic categorization and appropriate uplink data (traffic) compression algorithms resulting in the more effective use of uplink wireless resources	5g	Yes
[64]	Task Throughput	None	Graph-coloring-based technique for allocating optimum resources in which fog nodes transmit task requests from IoT devices to the base station	Fog Computing 5G	Yes

of IoT cluster data. However, the continuous increase in the amount of data transferred made the cloud unable to satisfy many IoT applications because of limited bandwidth. As a result, data near data sources need to be processed, and fog computing offers a promising solution to this problem [66]. Fog computing pushes the centralized nodes to logical methods of applications, services, data, computing power, and decision-making. Data volume that must move between the end devices and the cloud is significantly reduced by fog computing. However, fog computing alleviates some of the problems because potential IoT applications' performance, throughput, resources, and latency constraints cannot be met.

The approach suggested as architecture in [56] harnesses in a coherent archetype the advantages of IoT, fog, and cloud computing. The architecture is intended to promise IoT applications with faster response time. A layered design of the fog node can be adapted at the center of the design according to fog computing implementation specifications. For possibilities relevant to the future intelligent transportation infrastructure, the approach was applied experimentally.

The solution in [57] suggests using QoS management in a fog computing environment to improve the processing of data and decrease the required bandwidth. Five operating levels constitute the system hierarchy. The first is where sensor- and actuator-equipped IoT devices are mounted. Second level is responsible for environmental monitoring and regulation. The third stage, where fog computation takes place, ensures technical support and supervisory control functions. A composite view was prepared based on the short-term history of real-time functions. The fourth step guarantees that data processing arrives from below levels, which are supposed to have usable raw data information. The application-level was at the final level.

In [58], a latency issue was also addressed. This approach provides a method of resource allocation between fog network devices and IoT devices based on Qos. A two-sided matching game is formulated at the heart of the solution-based solution to initiate a user association, followed by resource allocation. The layout offers a contextual QoS calculation that can increase the efficiency of the corresponding result by prioritizing the application-specific QoS criteria while establishing the priority order of the players. Resource allocation and QoS provide high-demand networks with the necessary bandwidth.

Another approach that uses the matching theory in the fog network in [59] to maximize the node discovery and allocation of resources. Subject to maximal workload and latency restrictions, the authors developed an optimization problem for joint cloudlet selection and latency minimization in a fog network to execute the solution functions. A representation of the optimization problem of the matching game is many-to-one, in which IoT nodes and cloudlets are called players. To solve the matching game, a distributed and self-organizing algorithm results in an overall improved latency and throughput.

The authors propose an approach to the positioning of mini-clouds in [60]. The mini-cloud has been used in an IoT-based network to minimize the total data collection latency from IoT devices. A shared software-defined storage solution for IoT data integrating the concept of mini-clouds is the main component of the solution.Algorithms are programmed to transfer data between mini-clouds to solve mini-cloud storage capacity challenges, emphasizing that users requesting access to the data reduce access latency. The method of the solution is to start storing the data on the mini-clouds from the IoT devices/sensors. The computers/nodes comprise the mini-Clouds concept cluster. Then, to generate object storage, the storage on each node can be aggregated using a software layer abstraction. Each mini-cloud node acts as an IoT device/sensor application server.

Another resource management approach was suggested in [61] for dealing with connectivity problems in IoT devices. This approach is based on fog computation, which may assist resource management. Based on the nature of the device and mobility aspect, the approach grouped IoT devices into three and implemented resource management accordingly.

The proposed resource allocation mechanism in [10] is a swap-based three-tier fog network. The bottom layer comprises IoT end devices, an intermediate fog layer, and a back-end layer consisting of a core layer of a network and cloud datacenters. The solution also includes SDN nodes that allow extensive governance and continuous monitoring. A fog layer can minimize the delay because some network data can be processed near the bottom layer.

The advancement of 5th generation wireless communication is very encouraging to solve many IoT network connectivity problems [67]. 5G-enabled IoT-Gateways in [63] provide uplink IoT traffic classification, and optimum uplink compression strategies will help maximize the uplink load of traffic and result in optimal use of uplink wireless resources.

In [64], another approach aimed to optimize total heterogeneous tasks in the case of latency constraints covered by the 5G network. Presence of a graph-coloring algorithm is at the heart of the solution. The approach lies in this machine framework in which fog nodes relay the task requests of IoT devices to the base station for the central assignment of optimum resources.

Table 5 summarize connectivity solutions and give a brief insight about them.

C. SCALABILITY

Scalability is a system's ability to respond to environmental conditions and fulfill potential needs [73]. Two forms of scalability occur in IoT networks: horizontal scalability, which includes extending the network to support the increasing number of hardware equipment and software entities on the network, and vertical scalability, which is associated with the potential to build up the effectiveness of current software or hardware through the utilization of more resources [73]. Scalability approaches and strategies typically have to be framed as a sequence of steps.

One of the most common approaches for managing scalability criteria is a protocol-based solution. The authors' purpose architecture in [68] provides increased scalability and synchronization through wide-ranging IoT system sets interoperable across gateways. Gateways and IoT devices incorporate MQTT and CoAP to maximize node communication productivity for effective resource management based on a hierarchical arrangement of tree architectures. For inter-node connectivity in the hierarchical tree organization of IoT devices, the solution depends on MQTT. The solution

TABLE 6. Scalability solutions summary.

Reference	Specific Issue	Solution Name	Solution Summary	Involved Techniques	Implementation
[68]	Gateway Scalability	None	System to enhance scalability and minimize latency for communication across large groups of geographically distributed IoT devices using a dynamic tree structure organization, MQTT, and CoAP	MQTT CoAP	Yes
[69]	Large IoT Deployment	Software Defined Provisioning	Framework provides an IoT platform provisioning system, in which any device delivering data to services must be licensed and approved in order to communicate data	SDN	Yes
[70]	Large IoT Deployment	Cloud-Edge-Beneath	A cloud–sensor architecture with four layers for scalability in which sensor networks function autonomously and are connected to the cloud via a scalable number of Edge servers, while the cloud provides a scalable infrastructure due to cloud elasticity	Cloud Computing Edge Computing	Yes
[71]	Increase the scalability of LoRa networks	EWS	Technique to increase the scalability of LoRa networks by allocating resources depending on the distance parameter	Stochastic Geometry	Yes
[72]	Scalability in SDN	None	Platform analyzes the scalability performances of the suggested approach while accounting for the predicted growth of optical networks	M2M SDN	Yes

TABLE 7. Real-time processing solutions summary.

Reference	Specific Issue	Solution Name	Solution Summary	Involved Techniques	Implementation
[75]	Data Search	DiscoWoT	The extensible discovery method uses several discovery strategies to map web resources semantically and allows users to add to the available strategies at runtime	Web Technologies Semantic Discovery	No
[76]	Resources Search	None	A search-by-example technique to sensors in which the user offers a portion of its prior output as an example and seeks sensors that have previously provided comparable output	Fuzzy Logic	Yes
[77]	Resources Search	None	A framework for automated resource discovery in IoT integrates a search engine with the "look-up" capability for discovery	Web Technologies	No
[78]	Data Collection	DSNP	Data fusion technique for data summarizing in a node and via parameters given by an IoT application's server.	Data Fusion	Yes
[79]	Data Collection	MIST	A fog-based data analytics approach for IoT crowdsensing applications with cost-effective resource provisioning	Fog Computing Optimization Techniques	Yes
[80]	Data Processing	Firework	Method for enabling distributed data sharing and processing for IoT applications while keeping the data and computation inside the data facilities of stakeholders	Big Data Cloud computing	No
[81]	Data Collection	Recycle.io	Architecture for waste management systems in terms of improving recycling and disposal behavior by collecting data and detecting waste disposal problems in real-time.	Edge computing	No
[82]	Data Processing	None	Layered architecture for smart transportation systems using real-time big data and service management processing.	Big Data	Yes
[83]	Data Processing	None	A mechanism for employing IoT-based big data analytics to construct a smart city and urban planning	Big Data	Yes
[84]	Data Processing	None	A hybrid framework that combines big data, IoT, and semantic web to create an enhanced platform for the future of IoT applications	Big Data Deep learning	No
[85]	Context-Aware	None	A framework that combines IoT, context-aware systems, and the cloud allows environmental data to be sent from the lowest infrastructure level to a higher one for interpretation and decision-making	Cloud Computing Web Technologies	Yes

also uses MQTT to retrieve resource information and synchronize nodes in its tree management processes for interactions between the CoAP servers.

SDN is another way to acquire a scalable IoT environment. The solution in [69] seeks to build a system that can automatically trigger IoT devices and provisioning through SDN.

Each device that sends data to services must be provisioned and allowed to transmit data. In this context, the system functions as a continuous service filtering of the already stored SDN topology information and is used as a benchmark for application provisioning.

Cloud and edge computing are other ways of providing applications with scalability [74]. In [70], the perspective indicated how IoT systems could be constructed as multi-layer systems. Sensor platforms are low-power computing platforms and communication platforms that link physical devices and sensors to the edge. In practice, Edge may be a standalone server or computing system as an intermediate layer that links and operates a collection of sensors. The grouping of sensors is carried out according to form, feature, or position. Finally, the cloud creates, deploys, and operates sensor-based systems and software. This multi-stage structure has been planned to achieve scalability as sensor networks run independently and have a scalable number of edge servers linked to the cloud. In addition, there is a scalable infrastructure in cloud computing systems by definition.

To increase the scalability of LoRa networks, authors in [71] propose an exponential windowing technique (EWS). EWS is a method of allocating resources depending on the distance. It assigns a distance parameter in order to maximize the overall success probability of the LoRa network. Expressions for success probability are developed using stochastic geometry. The effect of exponential windowing and packet size on packet success probability is investigated.

Article in [72] targeted to examining the application of the OneM2M OCEAN open-source platform in the context of optical networks. Multiplexers, transponders, amplifiers, and monitors are instances of IoT devices. The authors' purpose was to analyze the scalability performances of the suggested approach while accounting for the predicted growth of optical networks, where the number of devices and monitors might significantly expand together with the pace of their generated updates. Furthermore, they designed the optical network controller as an IoT server platform that receives information from network elements and uses network status knowledge to reconfigure devices.

Table 6 presents a summary of the approaches proposed above.

D. REAL-TIME PROCESSING

IoT systems generate a significant amount of data, including measurements, system information, system state, and much more [86]. Processing these data is difficult because there are several problems or limitations in these data; these concerns, such as time and location complexity and heterogeneity, render the conventional big data processing methods unable to fulfill IoT data processing requirements. There is a need to boost real-time processing to provide efficient IoT systems. IoT real-time processing needs to reduce the lag period taken to obtain feedback and information from its participants by making their decisions nearly in real-time, based on the decisions of other services [86]. IoT must properly include resources for the processing and summation such enormous and extremely regular results. Real-time IoT processing requires several steps that must be performed concurrently or serially. These steps can include and not end with IoT resource discovery and search, data retrieval, data preparation, data processing, data analytics, and decision making.

In terms of resource discovery and search, the most relevant approach is the Web of Things (WoT) [87]. WoT is a framework designed to facilitate interoperability across IoT systems and application domains. The search and discovery feature is improved by leveraging multiple partners' evolved cooperation over several years. It has a unique architecture and terminology to define all IoT-based operations [88].

In [89], other search and discovery techniques were well analyzed. In this study, the search techniques were divided into indexing and clustering techniques, data representation techniques, and search content techniques. Other enhancements for WoT, such as IoTSEs, WoTSEs, Dyser, Shodan, SenseWeb, Thingful-IoTSVKSearchThingseek, and WoTSF, were also explored in this study.

DiscoWoT is another [75] search engine; it is a semantic web-based resource discovery tool that relies on several mapping schemes. The function of this search engine relies on semantically defining services that are understood to have network addresses. The core purpose of this search engine is to evaluate any relation to or description of a resource that a client submits using the registered strategies. The derived knowledge is used to construct an entity's internal model with organized data about the property, its properties, and its features. These details are forwarded to the user.

In [76], the authors proposed a resource identification and discovery system called an identification service for the similarity of sensors. This service can be used to identify areas with identical physical properties. The technique allows the user to install a new sensor, scan for similar output sensors, collect metadata of the identified sensors, and reuse proper fractions for metadata of the new sensor. The basis of this approach is a comparative algorithm based on fuzzy logic that frames the search for similarities in the sensor.

Established search engines are another approach that has recently attracted researchers. In [77], the work suggested a search engine-based resource discovery system for the Internet of Things (IoT) to discover objects, their abilities, properties, and URIs to access them independent of communication technologies. There is a single register to store the resource settings, and they are indexed. Based on the criteria for the discovery order, the search engine ''looks up'' the indices and returns the URI for direct access to the resources. The functionality of the proposed system was revealed to customers using RESTful web services.

Data collection and preparation is required for minimizing data transferred over the Internet, decreasing the amount of data processed in the program, and minimizing the energy usage of data delivery, storage, and processing. In this context, the solution in [78] suggests that a summary mechanism can contribute to local data fusion in the node. This technology addresses environments where a cloud storage system can store data. Node reads the necessary parameters to perform data summarization when attached to the application server in this environment. The method of summarization consists of an algorithm applied to the network, which the network sensor must use.

The study in [79] suggested a fog-based data analytics system for IoT crowdsensing applications with cost-effective resource provisioning. The key benefit of using fog in this architecture is that it allows data to be processed locally before being transferred to the cloud, which is very useful in minimizing data consumption. The proposed architecture separates computation into four layers: a layer of data generators, fog computing, cloud computing, and a layer of data consumption. Edge computing is an important enabler for real-time processing by delivering computations close to physical devices.

Architecture in [80] suggests a computational model that allows for distributed data storage and analysis for IoT applications while retaining the computation within the user's data facility. This architecture fuses geographically dispersed data by building virtual shared views of data accessible by data owners to end-users using predefined interfaces. The architecture also attempts to prevent data transfer from the edge of the network to the cloud and then reduce the latency in the response.

Serverless computing refers to the practice of offering backend services on a per-use basis [90]. Users may build and deploy code without worrying about the underlying infrastructure using a serverless provider. Serverless computing is a new approach to coping with real-time IoT and IIoT infrastructure issues.In [81], authors suggest a serverless Internet of Things (IoT) platform for optimizing the recycling and disposal behavior of waste management systems. The major goal was to gather violations in real-time, which would aid waste management firms and environmental protection organizations in conserving resources and determining perceived disposal costs. The proposed architecture should gather data and detect waste disposal infractions in real-time. The suggested framework employs Internet of Things (IoT) technology and edge computing capabilities to create a smart waste management system that can track recycling and disposal infractions.

Big data processing affects many real-time computing technologies. The purpose of the suggested architecture in [82] is to manage and analyze big data. Architecture is composed of three stages. In the first step, big data organization tasks are considered, including big data discovery, which initially includes IoT data, monitoring, integration, elimination, transformation, and cleaning. Step two is responsible for processing and analyzing big data. Big data processing is achieved using the parallel processing principle of the Hadoop ecosystem and MapReduce programming. Apart from Hadoop, the processing engine for Apache Spark is used for the efficient execution of a large data path. Final process is responsible for service administration, where advanced decision-making and event scheduling are carried out.

In [83], the framework implies a framework for monitoring IoT-based smart systems using real-time processing. A specific module is responsible for all tasks, from gathering data to filtering and making decisions. The data gathered and prepared are translated into an organized form that is understandable to the Hadoop ecosystem. Hadoop is used for batch processing, but Spark over the Hadoop framework was used for real-time analytics. Finally, decision-making is performed based on the findings provided by the Hadoop ecosystem.

IoT systems that combine many techniques, such as semantic approaches, cloud computing, AI, and big data analytics, will create an improved IoT environment that allows for efficient context awareness and decision-making mechanisms. Among several attempts in this sense, the [84] solution suggests big data analytics and learning a multi-layered system for conducting tasks such as gathering raw data from sensors, inserting a semantic and applying specific rules, applying specific learning methods, and finally taking actions. The system consists of five main layers, layers of data collection, extract-transform-load (ETL), semantic-rule reasoning, learning, and action.

Objective of the work in [85] was to monitor a remote automated device in real-time. System functions can collect situational information from sensors, analyze them, and make decisions about parameters. A specific module, called a context-aware middleware platform, executes these functions. The module mentioned above has four sections that work together to fulfill the system's specifications. First section comprises hardware components, such as individual sensors and sensor nodes in sensor networks. Cloud computing, including networks, servers, operating systems, and storage, is the second part. The third part is the network framework that allows users to connect to the cloud service on newly developed or acquired apps. Finally, the fourth section is the application entity.

Table 7 provides a summary of the solution related to real-time processing in IoT explained above.

E. MOBILITY

Mobility enables the IoT system to be available as it operates in internet-based domains. There are four main mobility objectives: data aggregation, coverage, accessibility, and energy nodes [95]. The mobility within the IoT is increasing exponentially as technologies proliferate. Additionally, mobility ensures a uniform balance between the load and energy consumption. It also decreases the number of hops necessary for transmitting information from the sensor nodes to the base station. Mobile nodes may also protect remote areas. These facets of versatility can minimize conflicts, collisions, and the loss of messages. The most important classification of IoT mobility is that IoT mobility is classified as sensor node mobility, event mobility, and sink mobility [95]. IoT properties, including memory space, processor ability,

TABLE 8. Mobility solutions summary.

Reference	Specific Issue	Solution Name	Solution Summary	Involved Techniques	Implementation
[91]	IP mobility	None	Provides a distributed algorithm for reestablishing communication sessions between peers in a reasonable timeframe	IP Technologies	Yes
[92]	Devices Provisioning	None	Develop a priority algorithm for ranking and processing IoT devices' messages sent and received	Cloud Computing	Yes
[93]	Mobility Prediction	None	Present a hybrid mobility prediction system that can forecast IoT device users' mobility	Deep Learning	Yes
[94]	Handover	UbiFlow	Demonstrate a lightweight IoT mobility system based on the coordination of distributed controllers spread over distinct geographic partitions	SDN	Yes

TABLE 9. Resource limitations solutions summary.

Reference	Specific Issue	Solution Name	Solution Summary	Involved Techniques	Implementation
[96]	Power Consumption	None	Edge prediction algorithms for delivering inferred information rather than raw data to minimize operations and energy consumption	Edge Computing Machine Learning	Yes
[97]	Processing Limitations	Lampda-COAP	An architecture for combining the IoT with cloud computing, which can help the IoT in terms of storage , processing, and networking	Cloud Computing	No
[98]	Bandwidth and Storage Limitations	None	Distributed learning model to reduce sending raw data from the distributed nodes to a central node	Edge Computing Machine Learning	Yes
[99]	Bandwidth Limitations	None	Model to learn the most suitable sampling intervals to reduce the number of transmissions and energy consumption	Machine Learning	Yes
[100]	Bandwidth Limitations	None	Machine learning-based system that provides dynamic spectrum access attempts to comprehend which channels are more likely to be accessible to reduce energy consumption.	Machine Learning	Yes
[101]	Power Consumption	Transport Triggered Architecture	A machine learning accelerator mechanism that is capable of applying an energy-saving feature	Machine Learning	Yes

and power supply, have limited IoT mobility management. Many ideas have been proposed that apply diverse methodologies to resolve mobility issues.

The solution in [91] suggests a policy that introduces sensors as endpoints to enable the mobility of the sensor and host on a different basis. The technique is built by a distributed peer-to-peer overlay network, which can easily restore contact between peers in transit and share information almost in real-time. The peer-to-peer framework retains an online presence in the temporary absence of mobile devices, allowing authenticated access to sensors by non-trusted hosts.

In [92], the authors suggested a method of exploration using techniques for data acquisition. This approach displays the closest IoT system that offers the network service for specific user demands. The solution consists of a parallel search method for IoT devices. The devices are categorized and organized in layers to simplify the request-resolution process depending on mobility frequency. In addition, a priority algorithm is a key to controlling and filtering the messages sent/received by the IoT devices, thus prioritizing the services provided by related devices. Priority of the request and reply messages is allocated based on predetermination, and the question is addressed by measuring the difference between the desired and available services.

Another solution to mobility needs can be anticipated using machine learning. The approach in [93] is based on principal component analysis (PCA) and a gated recurrent unit (GRU), which provide Wi-Fi and cellular data systems in an urban environment for predicting mobility. The solution acts as a positioning model to provide an advanced IoT system positioning output by combining the above algorithms. First, system gathers a computer LTE signal and Wi-Fi signal intensity from any Wi-Fi access point (AP) accessible and channels information from the Wi-Fi signal media. Second, the device uses a PCA to reduce the number of Wi-Fi and signal noise features. Finally, the GRU algorithm identifies patterns that can predict IoT computer user mobility.

In [94], a Software-defined IoT framework was introduced in heterogeneous urban networks for ubiquitous flow control and mobility management. This framework focuses on mobility management tasks, handover optimization, access point selection, and flow preparation through the collaboration of distributed controllers. The approach proposes splitting an urban SDN into separate regional partitions to obtain a dispersed regulation of IoT flows. A distributed overlay framework for network scalability and stability is proposed. The established controller differentiates the flow scheduling according to the specifications per system and the entire partition capability. The network status view can also be presented for optimized access point selection in multiple networks to fulfill IoT flow requests.

Table 8 gives an abbreviated description of the mobility solutions explained earlier.

F. RESOURCE LIMITATIONS

In general, IoT devices are resource-constrained; specifically, IoT devices have restricted processing, memory, and energy capabilities [102]. The IoT environment demands processing and storage resources to convert the data into usable information or services. Some applications will be latency-sensitive, while others, including historical data and time series analysis, require complex processing. The management of these resources is critical because of the stated limitations. Relevant enhancements in the IoT architecture or modifications to certain protocols may be used to manage IoT resources. Another approach is to incorporate other innovations that will be a key solution to the constraints mentioned above [102].

Cloud computing provides on-demand computational services, usually remotely and on an on-demand basis, from software to servers and processing facilities. Cloud computing can easily help bypass or decrease IoT system limitations.

The approach in [96] offers a novel collective machine learning platform at the IoT network edge to achieve scalability of the IoT edge network. Through machine learning on the edge of the network, the technique transfers only the inferred information that encapsulates and approximates the underlying data to the edge rather than transferring raw qualitative data into the framework. Overall, storage needs are minimized, and latency is reduced.

The work in [97] suggests an architecture that integrates IoT and cloud computing via lambda and middleware from CoAP. The goal of the architecture is to enhance the IoT with the required storage, processing, and networking capabilities, which could allow for the analysis and processing of large volumes of real-time data in IoT systems.

In [98], the solution tackled the issue of how the minimal computational and communication resources at the edge can be used effectively for optimum learning performance. They considered a traditional edge computing architecture in which edge nodes were linked through gateways to the remote cloud. The raw data were obtained and processed at multiple edge nodes. Moreover, a machine learning algorithm is trained from the distributed data without transmitting the raw data from the nodes to a central location. An algorithm to evaluate the frequency of global aggregation handles the solution such that the available resource is used more effectively.

In IoT systems, machine learning strategies can dynamically improve resource usage. Machine learning algorithm functions begin by monitoring the system's state and then generating the parameters that can dynamically change the system's behavior. In [99], the authors suggested an implementation scheme for online sampling intervals. The process relies on real-time analysis of the data provided by sensor nodes to adjust the WSN activity to the current environmental conditions dynamically. The purpose of the solution framework is to ensure a minimal amount of transmissions available to prevent missing useful environmental data. They attempt to hold the maximum difference between two successive calculation values below a particular value. Reducing the amount of transmitted data reduces the required storage, energy, and latency.

Similarly, the [100] approach introduces a technique for minimizing energy consumption by reducing the number of attempts to reach the medium of communication. The strategy for enhancing coverage focuses on machine learning. Instead of accessing the spectrum arbitrarily, flexible access to the spectrum based on reinforcement learning algorithms may expand coverage, decreasing the number of repetitions and thus lowering energy consumption.

In [101], the solution aims to achieve energy efficiency within the Internet of things (IoT). Implementing a machine learning algorithm on an IoT device rather than on a cloud is a way to achieve energy efficiency. A machine learning acceleration running at the level of ultra-low-voltage minimum energy is the suggested solution mechanism.

Table 9 summarizes the solution the target handling IoT resource limitations mentioned above.

V. OPEN ISSUES AND FUTURE DIRECTIONS

This survey addressed IIoT problems and proposed IoT solutions in the previous section. However, the proposed solution is insufficient to meet the IIoT's potential expansion and projected development. Some techniques must be adopted and focused on in the future of IIoT. Furthermore, the focus should not be entirely on implementing new methods but also on evaluating the adoption method, the feasibility of adoption, and the problems that may arise due to the adoption.

Based on the previous section's analysis findings, this survey focuses on three techniques for the future of IIoT: deep learning, edge computing, and big data. Following the general architecture discussed in the section. The proposed architecture of IIoT is depicted in Figure 6. Different modules are distributed throughout architecture layers in this figure. The edge layer is projected to be a critical component that can handle some deep learning and big data processing. The rest of deep learning and big data processing is planned to be done at the storage layer, which will have a lot of associated modules and ecosystems. Also, table 10 summarizes the general application of each technique, as well as the challenges to be tackled and open issues that need to be examined further in future work.

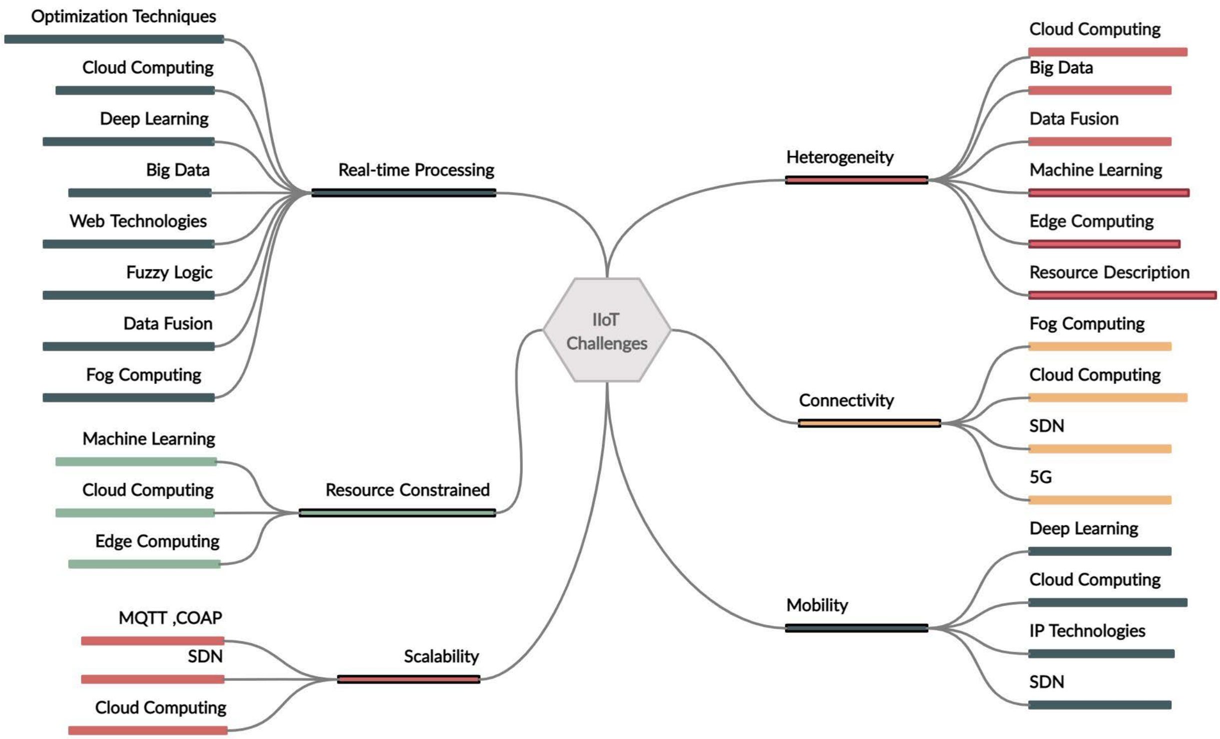

FIGURE 5. IIoT challenge and techniques summary.

TABLE 10. Summary of future techniques and open issues.

Aspect \Technique	Deep Learning	Edge Computing	Big Data
Usage in IIoT	1.Prediction for making future resource allocation 2.Prediction for potential maintenance 3.Classification of underlaying defects	1.Real -time data collection and analysis 2.Distribute resources utilization 3.Provide low latency communication	1.Provide data analysis 2. Distribute real time data computation
IIoT Challenges Tackled	1.Real-Time Processing 2.Resource Limitations	1.Resource Limitations 2.Real-Time Processing 3.Heterogeneity 4.Connectivity	1.Real-Time Processing 2.Heterogeneity
Open Issues	1.Reduce time consumption and models complexity 2.Use accelerator tools and approximation methods 3. Deep learning model optimization for federated learning.	1.Develop flexible mechanisms for the programmability of edge devices 2.Mange data offloading with minimal bandwidth and low latency 3.Leverging AI technique on the edge devices	1.Develop big data pipeline for large scale IIoT 2.Work on putting standardization for big data produced from IIoT systems

A. DEEP LEARNING

As the previous section shows, many solutions depend on machine learning as a core for their proposed solution. However, there are several drawbacks of machine learning, and the most complicated one is working with a new task that requires a large amount of data and features. The solution approach to the previous problem is to define the data input feature before implementing the machine learning algorithm. The approach mentioned above could lead to a high degree of bottleneck because there is a limit to what humans can do in defining the data features. Deep learning overcomes this bottleneck, and that is due to its capacity to classify the characteristics and representation of raw data itself. The term deep refers to the hierarchy of characteristics that ate and the ability to understand from the raw data itself [103].

The term deep refers to the hierarchy of defining attributes and the tendency to understand the raw data. Multiple layers called hidden layers are made of deep learning algorithms; these layers provide the model with feature extraction and learning methodology [104].

Feed-forward neural network is the foundation for all deep learning implementations; an input layer, hidden layers, and output layer are part of this network. Each feed-forward layer comprises a particular number of neurons receiving the data

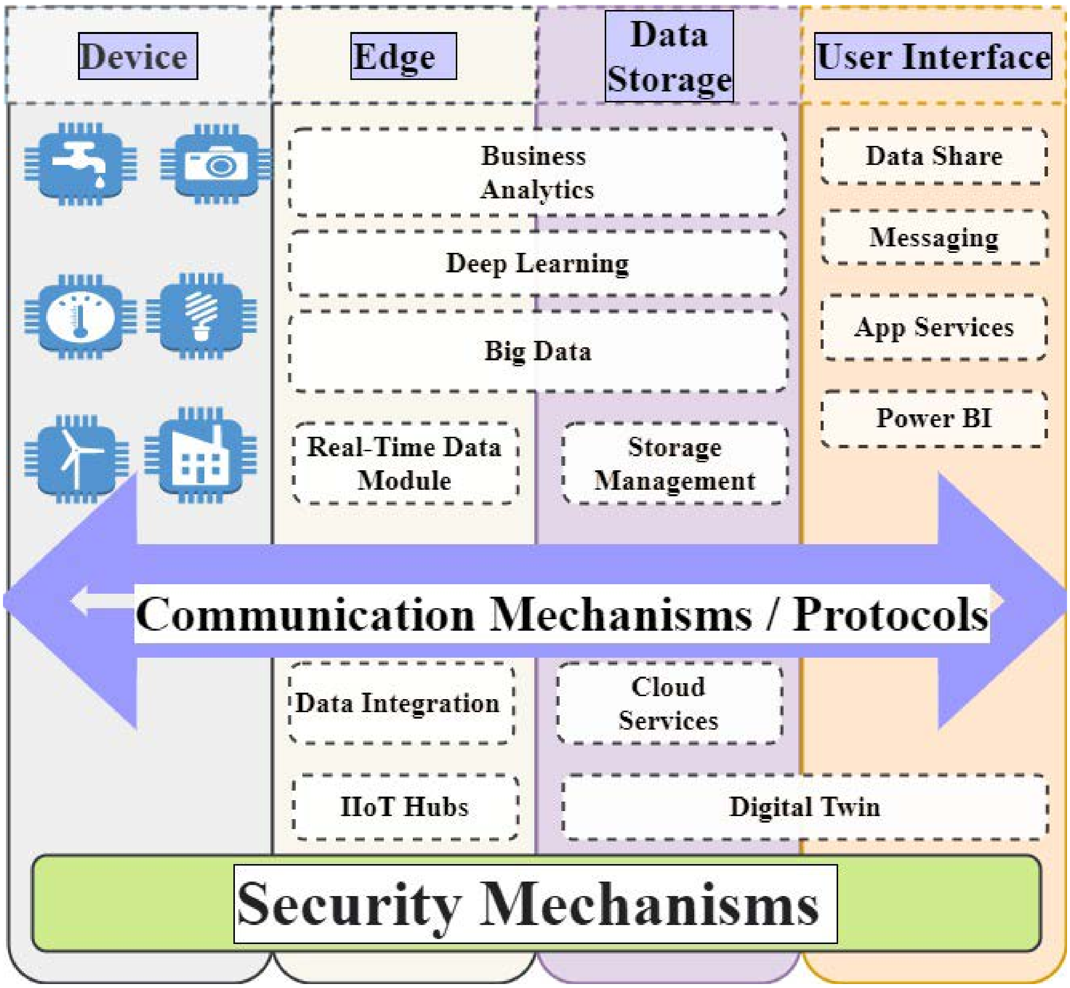

FIGURE 6. Potential IIoT architecture.

input, weights, and a bias value. The output is generated depending on the function called the activation function. An error is measured in the feed-forward neural network using the values given in the output layer. The purpose is to minimize these errors by changing the parameters (bias and weights) [104].

Recurrent neural networks (RNN) follow the same feed-forward neural network idea; the distinction is that RNN uses the "data memory" concept. Data memory involves storing the output value of various layers and transferring it to the cross-sequence steps of previous layers [105]. There is also an RNN extension called Long Short-term Memory (LSTM) [106]. LSTM uses a gating technique, and there is a hidden state created from the paste outputs. The gate takes the input and the hidden state as a reference for the activation function to generate a new input. The problem of vanishing gradient [107] can be overridden by LSTM.

Additionally, there is an important implementation of deep learning is the convolution neural network (CNN), where the data has high dimensions, which is challenging to handle with the classical neural network [108]. Various layers constitute the conventional CNN. Input Layer uses the input and feeds it to the next layer, which may have one or more dimensions. Convolution layer has particular size filters responsible for applying the convolution operation to data from the input layer. A convolution operation is applied if each filter scans the input data, and this scanning operation is applied to all data according to the filters and stride sizes. Pooling layer applies its functions after the convolution layer. This summary is typically performed by applying the max pooling operation, which selects a maximum value on the specified frame. A fully Connected Layer usually occurs at the end of CNN; this flattened input layer is such that all perceptrons are connected to each input. Along with the perception, the existence of this layer will optimize the precision of classification [103].

Deep learning becomes more important as the number of internet connected devices increases exponentially because these devices generate a large amount of data. [40], [104]. Because IIoT applications' performance is related explicitly to the intelligent analysis of big data from various real-time resources, both the amount of data and its features require proper consideration. Big data processing in IIoT networks thus includes intelligent modeling that can be performed using deep learning techniques [109]. In intelligent manufacturing, data modeling, labeling, and analysis play an important role [110]. Deep learning methods have emerged from automatic learning from the supplied data, finding patterns, and making correct decisions. IIoT can turn into highly efficient facilities with innovations generated by deep learning methods [104].

It is possible to locate IIoT data at three levels: smart devices, edge devices, and cloud. The deep learning methodology could be used to conduct quick analytics on the first two levels, while the deep learning algorithm could be applied on the third level for big data analytics [10]. For two purposes, classification and prediction, deep learning is primarily performed. Distinguishing unreliable and optimal systems based on observable evidence is an example of classification use. In terms of classification, CNN is beneficial in IIoT because it offers detailed information (in terms of attribute extraction) using multiple datasets with limited manual intervention [35]. Classification helps the industrial process to use its visual flaw detecting capability to be reliable and accurately recognize the underlying defects [104].

Prediction, on the other hand, encourages the maintenance to be carried out before any potential failure. In IIoT, RNN can be used efficiently to predict possible problems with various system health parameters. It can assist smart factories where future predictions can reduce the total cost of development and increase the product's downtime [104].

The most important problems that were recently addressed or solved using deep learning approaches are real-time processing and resource limitations challenges as follow:

1) Data analysis is the method optimally controlled using deep learning. Data analysis is an immediate solution for real-time processing frameworks [111].
2) Predictive analytics provided by deep learning can utilize statistical models and provide the prospect of making future resource allocation based on the provided historical data, which can lead to an efficient mechanism for minimizing the resources required to execute jobs [109].
   Deep learning predictive analytics can also use mathematical models to allocate potential resources depending on the historical data presented [104], [109].
3) Federated Learning (FL) is another key area where deep learning might influence IIoT applications. FL is a deep learning paradigm that has many advantages in training diverse and private data [18]. By isolating the central server's direct access to the original data from the model training, FL limits the leaking of users' personal private information to some level. Furthermore, FL can successfully retain data heterogeneity, and decrease model training deviation [18], [112]. Each IIoT device may train its model based on locally obtained data using the FL method. The data from IIoT devices do not have to be sent to a centralized cloud. Individual users must only provide the updated local training model to the centralized cloud [113].

The integration of deep learning into IIoT faces certain constraints. One of these concerns is the performance problem arising from the time consumption of the training process and the computing demand due to the complexity of the model and the broad industrial dataset [109].

Processing of input data to the chosen model is another challenge, which may require several steps, such as translating the messy data containing missing values, outliers, and valueless entries to the type of data known by statistics and algorithms for deep learning.

Recently, several methods have been developed to help overcome the above problems. The application-specific instruction processor (ASIP), application-specified integrated circuit, FPGA, or co-processor can be used to accelerate deep learning algorithms [10]. Approximate computation, which could require missing less important characteristics, may be effective. Finally, another solution is to share algorithm computation among the hidden layers [10].

B. EDGE COMPUTING

Edge computing is a distributed network technology in which processing takes place close to the actual location where data are collected and processed, rather than on a centralized server or in the cloud [34]. Edge computing is significant because it helps industrial and enterprise companies find new and easier ways to enhance operating productivity, boost performance and protection, automate all key business operations, and ensure "always-on" functionality. It is one of the most effective ways of accomplishing digitalization. However, there have been various edge computing deployments in recent years, as mentioned above. Mobile cloud computing (MCC) is one of the listed implementations. It is based on delegating storage and computation to remote entities to minimize workload and maximize energy usage, lifespan, and expense objectives. Mobile edge computing (MEC) is an edge computing concept that takes cloud computing technology to the mobile network's edge and is another implementation [8].

Edge computing and cloud computing work together to employ a scalable approach depending on each organization's data processing and analysis requirements. At certain workloads, the edge is suitable for real-time collection and analysis [34]. Simultaneously, the cloud can act as a central location for large-scale analytics. As a result, edge computing perfectly meets the need for real-time processing, especially for time-sensitive applications. Edge computing infrastructure can be successfully associated with IIoT, involving sensors to gather data and edge nodes to safely process data in real-time on-site while still linking other devices to the network, such as smartphones and laptops [8]. Because the edge architecture is conscious of customers' needs and goals, it distributes more efficiently networking, connectivity, power, and storage resources around the cloud spectrum, resulting in implementations that help fulfill clients' requirements [114].

Low latency is achieved owing to the edge architecture, which facilitates data transmission and storage near the device.

Resource limitations, real-time processing, heterogeneity, and connectivity are mostly a range of challenges that edge computing has successfully addressed recently and are expected to continue in potential solutions [114]as follow :

1) Edge computing can be adopted to reduce working memory, which can help with resource constraints. IIoT systems typically generate an increasing volume of data, which can then be moved and stored at the edge based on established requirements, allowing devices to reduce the impact of resource constraints [114].
2) Edge computing and data analytics can also be used to solve real-time processing issues. The most obvious way to achieve this is to create data analytics systems and platforms that move some of the data collection features that were formerly implemented in the cloud to the edge, allowing for better real-time data analysis benefits [34].
3) Massive amounts of real-time data are normally implemented in IIoT, both in terms of communication and the necessary intelligence for process management. Initial sensory data can be processed near sensor nodes using edge computing in IIoT, minimizing query time. Nonetheless, effective and reliable routing techniques will minimize overhead while still lowering latency [8].
4) The top design of data and resources is concerned with task scheduling; this entails deciding how data should be sent throughout the network and how resources should be partitioned and used [35]. For task scheduling, the energy-latency tradeoff must also be taken into account. Some techniques are proposed to decrease end-to-end latency in extant research on edge computing job scheduling in IIoT. The solutions mostly focus on creating or developing algorithms that allow edge computing to contribute to task execution by relocating part of these jobs to the edge.

Although several issues must be dealt with properly to make the integration of edge with IIoT more apparent, one of the issues listed in [110] is the programmability of edge devices. The issue of programmability is a significant difference in versatility between cloud platforms and edge tools that must be bridged. Second, naming schemes that can accommodate many devices that need to be provided by the edge.

Another problem that must be considered is the data offloading. In edge computing, data offloading is widely used to offset a system's total load, resulting in high latency in the edge network, high bandwidth resource utilization, and, eventually, possible task delays increase.

To make the industry environment smarter and more important, AI techniques may typically be trained to make correct assumptions and decisions. However, large volumes of testing and verification data are required. Given the limited computational and storage capacity, teaching and leveraging the AI model on edge devices is challenging. In addition, several security and privacy issues, data abstraction, service management, and optimization issues have been addressed in the literature [115], [34], [8], [114].

C. BIG DATA

The expression "Big Data" illustrates various concepts, ranging from the processing and aggregation of large volumes of data to a variety of sophisticated digital tools aimed at revealing trends in human behavior. Big data is a collection of different granular data types produced by various applications, such as the Internet of Things (IoT), self-quantified multimedia, and social media data, resulting in large volumes of data [116].

Big data implementation must operate in parallel with the organization's supporting infrastructure, which generates increasing volumes of data from many sources that are not well organized or easy, such as data from computers or sensors, as well as large public and private data sources [116]. Previously, most enterprises could not collect or retain significant volumes of data. Existing computing tools are also incapable of delivering full results over time. New big data innovations, on the other hand, have aided in performance enhancement, product growth, and operation and decision-making support [116].

Two considerations drive the use of big data tools in any system. The first reason for big data adoption is cost savings. Using big data solutions such as Hadoop and cloud-based analytics can save businesses money when vast volumes of data need to be processed, which can also help businesses find more effective ways of conducting business. Another factor is time; technologies such as Hadoop and in-memory analytics will quickly discover new data sources, allowing companies to analyze data and make fast decisions based on their findings [12].

For IIoT big data, efficient and effective analytic solutions are required across various industrial applications. The current focus is on developing efficient and effective systems that can manage the unique characteristics of IIoT large data [117]. Regarding applying big data to IIoT, staging approaches similar to those used in big data models are expected. The first stage entails dealing with raw data, which requires more analysis to increase accuracy and maintain consistency with IIoT applications [12]. In the case of historical data, data wrangling and cleaning methodologies aid in collecting relevant datasets. In contrast, in the case of streaming data, data sources assist in selecting appropriate data streams. The next stage includes numerous big data preprocessing processes, which are defined using mathematical methods to effectively manage unstructured, unbalanced, and non-standardized data points. Data analytics plays a part in the third stage to generate learning models from high-quality, well-prepared data. Model rating operations are carried out after the model has been developed by supplying sample datasets and finding and grading the attributes in datasets/data sources [116]. In IIoT systems, the final stage typically includes automatic data pipelines. The data pipelines must be constantly checked for changes, and the entire device process must be re-executed to achieve high-quality performance.

Big data methods are expected to solve the difficulty of real-time computation and heterogeneity as described in the following points :

1) Big data can provide high-precision data analytics, the cornerstone for IIoT data processing, especially in real-time modes. Big data are generated by IIoT systems, which produce many raw data sources. As a result, real-time data processing will boost system health and result in defect-free component production in real-time [3].
2) Big data on the IIoT can help solve the problem of heterogeneous data that is spatially connected at times. Traditionally, several data integration forms have been used to handle this problem, which necessitates the definition of correct data adapters based on a perception of sources scheme [118].

The integration of big data into IIoT significantly affects a given industrial system's requirements; thus, big data processing can occur at the sensing, edge, or cloud levels [3]. Despite the future IIoT openness, big data servers, including distributed servers, will follow a service trend, with data storage and computational power available to customers as utilities. In future IIoT, a programming environment will be developed in which users can create applications based on desired features. Online or smartphone apps can freely download necessary data from the big data registry and register computing tools from the big data portal for data analysis and processing. Computation resources are saved, and device scalability is greatly expanded in future IIoT by converting big data into scalable services [12].

Since implementing big data processes is mostly in its early stages. Future studies will need to look at certain limitations. Existing systems may not be consistent with industry-wide or multi-industry requirements. New standardized principles are needed to define the kinds of big data that industries should receive from consumers, how data can be protected, maintained, and exchanged, and who can benefit from it [12].

Scalability is another attribute that should be cautiously considered because large-scale IIoT networks are typically difficult to install, configure, track, and manage. Furthermore, an end-to-end industrial analytics pipeline that can manage big data from multiple data sources in parallel and identify highly correlated information patterns that appear across all IIoT systems is needed [116].

VI. CONCLUSION

Industry 4.0 is now widely recognized as a paradigm shift in society. This survey provides a solid overview of the state debate in the manufacturing community about Industry 4.0 and the role of IIoT. This survey examines the current state of Industry 4.0 in terms of concept, requirements, and supporting technology and the relationship between technologies and requirements. Regarding IIoT, there is a brief discussion of the IIoT and the architecture and use cases. In addition, we provide a comprehensive review of IIoT challenges in the community, including the main issues, approaches, and techniques. According to our survey, heterogeneity, real-time processing, mobility, resource limitations, connectivity, and scalability are the main obstacles IIoT implementation faces in industry sections. Finally, we addressed the technologies that are needed and critical for future IIoT and Industry 4.0 cooperation and the open issues related to them, in addition to exploring the potential architecture of IIoT, including deep learning, big data, and edge computing.

In our future work, we intend to investigate the role of blockchain in securing data based on the future architecture of IIoT.

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