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Impact of Federated Learning on Industrial IoT - A Review

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Abstract: The convergence of the Industrial Internet of Things (IIoT) and Artificial Intelligence (AI) has given rise to Industry 4.0, creating a wealth of opportunities for manufacturing companies. Nevertheless, the adoption of this paradigm shift, particularly in smart factories and production, is still in its early stages and faces several obstacles, such as substandard data quality and fragmentation, resulting in limited insight driven IIoT innovation. To overcome these challenges, this article highlights a decentralized architecture that utilizes emerging multi-party technologies, privacy-enhancing techniques like Federated Learning, and AI approaches. The proposed approach strives to establish a cross-company collaboration platform and a federated data space that addresses the fragmented data landscape. Federated Learning is one way to enable the sharing of confidential data generated from various IIoT devices. However, traditional Federated Learning raises privacy concerns. This review introduces the basics of FL, describing its underlying implementation of technologies, advantages and disadvantages, and recommendations, along with privacy-preserving methods. Most importantly, this work contributes to comprehending a broad range of FL current applications and future trends in technology and markets today.

Keywords: Federated Learning, Cybersecurity, IoT, Edge Computing.

I. INTRODUCTION

The Industrial Internet of Things (IIoT) refers to the use of internet-connected devices and sensors in industrial settings to collect and exchange data, monitor and control processes, and enable more efficient and effective industrial operations. IIoT is a key application of IoT technology and is driving the transformation of traditional industrial processes by enabling greater automation, intelligence, and optimization. IIoT devices can be used in a wide range of industrial applications, including manufacturing, transportation, energy, agriculture, and healthcare. Examples of IIoT devices include sensors that monitor temperature, pressure, humidity, and other environmental factors, as well as devices that control and monitor machinery, such as robots and conveyor belts. The benefits of IIoT include improved operational efficiency, enhanced safety and security, and greater insights into industrial processes. By collecting and analyzing data in real-time, IIoT devices can help organizations optimize their operations, reduce costs, and improve product quality.

II. INDUSTRY-SPECIFIC APPLICATIONS

A. Pharmaceutical

The pharmaceutical industry seamlessly leverages the power of the Industrial Internet of Things (IIoT) to augment the quality of its products and the manufacturing process. IIoT sensors capture real-time data on crucial aspects such as temperature, pressure, and humidity, which are then utilized to optimize the production process. Consequently, the manufacturing process is streamlined, minimizing errors and improving overall efficiency [1].

Incorporating IIoT sensors can not only monitor equipment but also predict maintenance requirements before any breakdown occurs. This proactive approach helps to minimize downtime and maintenance expenses while optimizing equipment performance. In addition, IIoT sensors effectively monitor product quality at every stage of the manufacturing process, guaranteeing that the final product meets the necessary quality criteria. This reduces the likelihood of product recalls and increases customer satisfaction levels [2]. Moreover, IIoT or Industrial Internet of Things can optimize the pharmaceutical supply chain, from raw materials to finished products. This technology ensures timely delivery of products, improves inventory management, and reduces lead times. IIoT can also monitor patient health in real-time through wearable devices, collecting vital sign data and sending it to healthcare professionals. The implementation of this methodology results in a reduction in healthcare expenditures and an improvement in patient outcomes. Its implementation is a mutually beneficial solution. [2, 3].

Recent research has put forward comprehensive frameworks incorporating IIoT with cloud computing, big data analytics, and AI to boost productivity, prevent downtime, and ensure product quality. The implementation of IIoT in the pharmaceutical sector has facilitated live supervision of production data, machinery state, and quality control, resulting in noteworthy enhancements to the manufacturing process[4]. The pharmaceutical industry can significantly benefit from using the Industrial Internet of Things (IIoT) to improve its manufacturing process[5]. A recent study proposes a framework integrating IIoT with cloud computing, big data analytics, and AI to enhance efficiency, reduce downtime, and ensure product quality. The study found that IIoT enables real-time monitoring of production data, equipment status, and quality control, which can significantly improve the pharmaceutical manufacturing process.[5]

B. Industry 4.0

The era of industrial operations is being transformed by the Industrial Internet of Things (IIoT), which brings with it increased levels of automation, intelligence, and optimization. With advancements in IIoT, traditional industrial processes can be reshaped, leading to innovation and increased productivity and efficiency across various industrial sectors. In this landscape, federated learning appears to be a promising solution. It enables IoT devices to share data and collaborate while maintaining user privacy. This decentralized machine-learning approach eliminates the need for centralized data storage or processing, instead training machine-learning models on data from multiple devices [6]. In the IIoT context, federated learning has the potential to revolutionize the collection, analysis, and use of data in industrial environments. Machine learning algorithms can gain insights from locally generated data on individual devices, addressing privacy, security, and bandwidth limitations that are common in industrial settings. Federated learning enhances the precision and efficacy of predictive models. It achieves this by enabling models to be trained on a diverse array of data sources, which results in more accurate predictions and quicker response times in industrial procedures [8].

Federated learning is an effective strategy to improve scalability and resilience in IIoT systems. The distribution of data processing and analysis across multiple devices brings several benefits. Firstly, it reduces the burden on central servers, leading to faster and more efficient data processing. Secondly, it ensures uninterrupted operations even when servers are down or there are network outages. This enhances system reliability, minimizes downtime, and prevents data loss [9]. Federated learning has significant business potential for organizations in this domain. By providing real-time data analysis at the network edge, federated learning offers valuable insights into operations, leading to process optimization, cost reduction, and improved product quality [10,11].

C. Manufacturing

The use of IIoT in manufacturing goes beyond the pharmaceutical industry. Researchers have put forth models that utilize IIoT data to improve production processes in a flexible manufacturing system (FMS). Wang et al. [12] developed a dynamic workflow scheduling model that utilizes IIoT data to optimize production processes in an FMS, leading to a significant reduction in cycle time and a productivity improvement. In addition, manufacturing plants can enhance energy efficiency by utilizing IIoT data. Yaseen et al. [13] proposed a framework that utilizes IIoT sensors to monitor energy consumption in real-time and apply optimization algorithms to reduce energy waste. The framework can reduce energy consumption by up to 30% while maintaining product quality and throughput. IIoT is a game-changing technology that can optimize the production processes for steel coils. According to Zhang et al. [14], implementing a cutting-edge system that utilizes IIoT sensors can revolutionize the steel production industry by significantly improving efficiency and quality control measures. This system closely monitors the temperature and humidity levels of steel coils during production. It employs advanced machine-learning algorithms to predict defects and optimize production parameters. The study found that the proposed framework can significantly improve the quality of steel coils and reduce waste. Therefore, it is clear that IIoT has the potential to transform the steel production industry and bring about substantial benefits. These studies demonstrate the potential of IIoT to optimize manufacturing processes across various industries, resulting in improved productivity, energy efficiency, and product quality. Incorporating the Industrial Internet of Things (IIoT) in manufacturing systems facilitates constant and immediate data tracking and examination, empowering organizations to make decisions based on data insights and optimize operational effectiveness [15].

D. Agriculture

In a recent study conducted by Li and colleagues [16], the use of the Industrial Internet of Things (IIoT) for smart agriculture was investigated. The researchers proposed a framework that combines IIoT with cloud computing and artificial intelligence (AI) to optimize crop growth and boost productivity. The study found that by using IIoT and other advanced technologies, farmers can achieve higher-quality yields and reduce resource consumption, leading to sustainable and cost-effective agricultural practices. These findings highlight the versatility of IIoT in different sectors and emphasize the benefits of integrating it with other cutting-edge technologies like AI and cloud computing. As a result, we can expect Industry 4.0 to flourish and transform how businesses function, particularly in the agriculture sector.

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III. IMPLEMENTATION OF FEDERATED LEARNING ON INDUSTRIAL IOT

Overall, federated learning has the potential to significantly impact the IIoT by enabling more accurate and efficient machine learning models, improving system scalability and resilience, and providing organizations with more significant insights into their operations. Existing research on the Industrial Internet of Things (IIoT) covers various topics, including its benefits and challenges, use cases, and technologies. One central area of research has been the benefits of IIoT for industrial processes [17,18]. Studies have shown that IIoT can enable greater automation, improve operational efficiency, reduce costs, and improve product quality. For example, IIoT devices can help monitor and optimize equipment performance, reduce downtime, and improve supply chain management. Another area of research has focused on the challenges of implementing IIoT, including data privacy, security, and interoperability issues. Studies have highlighted the need for robust security measures to protect IIoT devices from cyberattacks and the importance of standardization and interoperability to ensure that IIoT systems can communicate effectively. Researchers have extensively studied using specific technologies such as edge computing, cloud computing, and artificial intelligence in IIoT. These studies have delved into how these technologies can be integrated into industrial systems and utilized to process and analyze IIoT data [19,20]. Furthermore, research has been undertaken to determine the economic impact of IIoT, with studies estimating its potential value for industries such as manufacturing and logistics. In summary, the current research on IIoT demonstrates its ability to revolutionize industrial processes and increase productivity and efficiency. However, it also highlights the importance of addressing the challenges and limitations associated with implementing IIoT systems and developing effective strategies for managing and analyzing the vast amounts of data generated by IIoT devices [16].

IV. EXISTING IOT STRUCTURE

IIoT implementations rely on architectural patterns that provide a framework for creating practical solutions. These widely recognized patterns include the three-tiered pattern, gateway-mediated edge connectivity and management pattern, layered data bus pattern, and system of systems architecture pattern. These patterns offer abstract perspectives of IIoT system implementation that are commonly repeated while allowing for variations. For example, the three-tier IIoT system pattern allows for multiple tiers and connections among them, but each tier is only represented once in the pattern [21].

A. Three-Tier Architecture

A three-tiered architecture is a system comprised of three tiers: the platform tier, the enterprise tier, and the edge tier. Each tier has specific data flow and control responsibilities as part of its usage tasks. These tiers are connected through three networks, as illustrated in Figure 1. The edge tier gathers data from edge nodes through a proximity network. Its characteristics include managing proximity network characteristics such as location, governance, and distribution, depending on the specific requirements of each use case. The platform tier is responsible for receiving, processing, and forwarding control commands sent by the enterprise tier and received by the edge tier. It combines processes and analyzes data flow from the edge tier and other tiers. This tier also handles device/asset management functions and provides general services such as analytics and data queries. The enterprise tier is responsible for implementing domain-specific applications, decision support systems, and providing end-user interfaces. It receives data from and sends control commands to the platform and edge tiers.

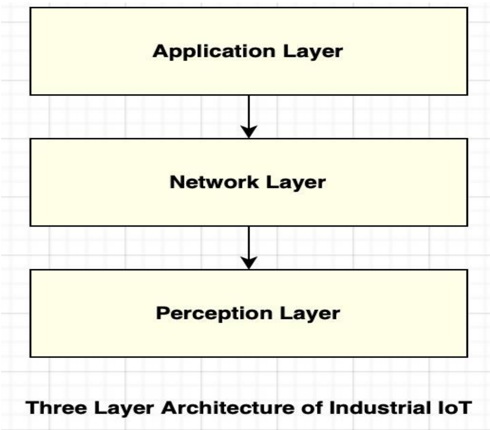

Figure 1

B. Gateway-Mediated Edge Architecture

The Gateway-mediated edge connectivity and management architecture pattern is a system that employs a gateway to extend a Wide Area Network (WAN) and provide local connectivity for the IIoT edge. By acting as a WAN endpoint

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and separating the local edge network, this pattern allows for localized controls and operations, including computing and edge analytics. The main advantage of this pattern is its ability to simplify the IIoT system, making it easier to scale the network and manage assets. However, it may not be suitable for systems with mobile assets that cannot form stable clusters within the local network. Additionally, the edge gateway can function as a device and asset management point and a location for data management where data aggregation, analytics, processing, and control logic can be performed locally.

V. FUNDAMENTALS OF FEDERATED LEARNING

Federated Learning (FL) is an innovative branch of AI that involves training ML models on data stored on decentralized devices such as sensors, phones, and smart devices. FL offers a way to train models without exchanging data samples between devices, ensuring privacy and security. The core principle of FL is that ML models are trained on local data. Then, the model's parameters are exchanged between the local nodes (devices) at regular intervals, creating a global ML model. Crucially, the training data remains on individual devices, and only the model updates from local devices are sent to the central cloud storage. The global ML model resides on a server. Once all devices have sent their models to the server, a combined model is created by averaging the parameters of individual models. This collaborative approach allows individual devices to learn from a shared model. FL offers several advantages over traditional ML models, including enhanced data privacy, reduced latency, and reduced power consumption. Not only does FL ensure the privacy of users' sensitive information, but it can also provide personalized ML models that enhance the user experience.[22]

VI. MOTIVATIONS OF INTEGRATING FEDERATED LEARNING WITH IIOT

The rapid expansion of IIoT applications is facing several obstacles, including security, privacy, and communication costs. The integration of FL with IIoT presents a promising solution to these challenges. The following are the primary reasons for integrating FL with IIoT applications.

A. Security and Data Privacy Preservation

Companies operating in Industrial Internet of Things (IIoT) applications heavily depend on implementing machine learning and deep learning algorithms to extract valuable insights and patterns from the data generated by IoT devices. This involves regular training of algorithms on large datasets collected from various industries and locations, which poses a significant risk to sensitive data being transferred to a central location for training. This is because potential hackers and intruders may gain access to confidential business information [23]. To address this concern, Federated Learning (FL) offers a viable solution that allows algorithms to be trained securely without transferring datasets to a central location. FL adds an extra layer of security to protect sensitive data from potential attackers and preserves data privacy. By eliminating the need to transfer sensitive data to a central location, federated learning effectively reduces the risk of unauthorized access to data.

B. Reduced Communication Cost

The use of sensors in IIoT generates massive amounts of data, which can result in high communication costs when transferred to the remote cloud. FL offers a solution where only summarized results of the data after application of ML/DL models are transferred to the cloud, reducing communication costs. FL enables the transfer of only a few instances of data to the central cloud, thereby decreasing the amount of data transferred from local devices to the cloud.

C. Improved Performance of the Network

To effectively handle the copious amounts of data generated by IIoT devices, a robust network infrastructure is essential. However, this may lead to performance issues. Using an FL configuration, ML/DL models can be applied to data generated by IIoT applications, which are stored in edge devices. This allows for the transmission of only summarized results to the central location, effectively reducing network traffic and improving overall network performance [24].

D. Scalability

IIoT devices generate a large amount of data, and conventional ML algorithms struggle to handle such big data. However, the integration of FL with IIoT allows DL algorithms to scale their learning without being trained on large volumes of data generated locally. The central algorithm is trained only on summarized results from the individual edge devices, which allows the central learning algorithms to scale significantly and train from the data generated at several edge/local devices [25].

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VII. DRAWBACKS

Although Federated Learning (FL) presents numerous benefits, such as data confidentiality and reduced communication costs, it poses specific challenges when applied to Industrial Internet of Things (IIoT) environments. One major issue is the potential for increased latency. FL relies on exchanging model updates between devices, and this process may introduce delays that can impact real-time responsiveness, which is critical in industrial settings [26]. Additionally, the decentralized nature of FL may cause problems with model synchronization, potentially compromising the overall system accuracy. Ensuring all devices maintain consistent and up-to-date models is a technical challenge [27]. Moreover, FL can face scalability issues, particularly in large-scale IIoT deployments. As the number of devices grows, managing federated models becomes increasingly complex, potentially straining network resources and computational capabilities [28].

Recent studies have shown that FL is vulnerable to adversarial attacks. Given that IIoT systems are crucial to critical industrial processes, it is essential to ensure the robustness of FL against malicious activities. Hostile attacks during the federated learning process can threaten the integrity of the learned models [29]. In summary, although FL provides promising solutions, its application in industrial IoT is accompanied by challenges related to latency, model synchronization, scalability, and susceptibility to adversarial attacks. This highlights the need for further research and optimization in this evolving field.

VIII. CONCLUSION

The convergence of IIoT and AI offers a transformative opportunity for manufacturing companies, but challenges such as substandard data quality and fragmentation hinder innovation. Federated Learning (FL), a decentralized machine-learning approach, offers a unique solution to facilitate cross-company collaboration, establish a federated data space, and address the fragmented data landscape. FL can enhance data privacy, security, and scalability in pharmaceuticals, manufacturing, and agriculture. The implementation of FL in the IIoT landscape aligns with current research highlighting the benefits of IIoT, emphasizing its ability to revolutionize industrial processes. By adopting FL in the IIoT, organizations can mitigate the risks associated with centralized data training, ensuring sensitive information remains secure. The reduction in communication costs, improved network performance, and scalability make FL a strategic choice for organizations looking to harness the full potential of IIoT in a secure, efficient, and scalable manner.

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