SWARM LEARNING: A SURVEY OF CONCEPTS, APPLICATIONS, AND TRENDS

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ABSTRACT

Deep learning models have raised privacy and security concerns due to their reliance on large datasets on central servers. As the number of Internet of Things (IoT) devices increases, artificial intelligence (AI) will be crucial for resource management, data processing, and knowledge acquisition. To address those issues, federated learning (FL) has introduced a novel approach to building a versatile, large-scale machine learning framework that operates in a decentralized and hardware-agnostic manner. However, FL faces network bandwidth limitations and data breaches. To reduce the central dependency in FL and increase scalability, swarm learning (SL) has been proposed in collaboration with Hewlett Packard Enterprise (HPE). SL represents a decentralized machine learning framework that leverages blockchain technology for secure, scalable, and private data management. A blockchain-based network enables the exchange and aggregation of model parameters among participants, thus mitigating the risk of a single point of failure and eliminating communication bottlenecks. To the best of our knowledge, this survey is the first to introduce the principles of Swarm Learning, its architectural design, and its fields of application. In addition, it highlights numerous research avenues that require further exploration by academic and industry communities to unlock the full potential and applications of SL.

Keywords IoT, Blockchain, Swarm Learning; Edge Computing, Security, Decentralized Machine Learning, Federated Learning, Privacy Preservation

1 Introduction

The next five years are expected to witness a significant increase in the number of IoT devices. In 2019, the healthcare sector utilizes one-third of all IoT devices, which are expected to climb to 40%, or $6.2 trillion, of the total global IoT technology market value by 2025 [1]. The global adoption of IoT devices is expected to reach 29 billion by 2030, covering a wide range of economic sectors and disciplines [2]. Particularly, IoMT devices are poised to save $300 billion, predominantly in the chronic illness and telemedicine sectors. This market is considered attractive for investors, with projections that estimate revenues of $135 billion by 2025 [3]. Moreover, the global healthcare market is expected to grow to $6.2 trillion by 2028 [4], necessitating advancements in AI, resource management, data processing, and

knowledge mining. The rapid advancement of the 5G standard and Multi-Access Edge Computing (MEC) has markedly improved productivity [5].

Modern deep learning models are raising concerns about privacy and security due to their reliance on centralized servers to store large datasets [6]. Although cloud-based local learning allows some level of collaboration and improvement of results, it introduces several inherent challenges to this centralized approach, such as data redundancy, increased data traffic, and increased security and privacy risks. Two primary challenges associated with traditional centralized learning methods are data ownership and privacy [4]. Federated learning (FL) emerges as a viable solution to these challenges, potentially aligning with data protection standards that could conflict with traditional centralized learning approaches [7]. FL promises notable improvements in security, fairness, and transparency, setting a new benchmark for digital data management and model training [8].

FL facilitates collaborative learning that preserves privacy. It addresses central data storage issues by allowing the raw data to remain on local devices at each participating node [5],[9],[10]. However, FL is still vulnerable to sophisticated cyber threats, including membership inference and data reconstruction attacks, which pose significant risks of data breach. FL also has limitations in network bandwidth that cause delays. To mitigate these vulnerabilities, two approaches are introduced: 1) Distributed FL (DFL [11]) and 2) a novel approach called Swarm Learning (SL) that was developed in collaboration with Hewlett Packard Enterprise (HPE[6]).

DFL and SL are approaches to machine learning that improve privacy and reduce reliance on centralized data storage. DFL extends the traditional federated learning model by allowing multiple nodes to train models collaboratively without a central server[12],[13], [14], while Swarm Learning uses blockchain technology to create an autonomous peer-to-peer network without a central authority. Both approaches aim to decentralize learning and enhance privacy, but SL employs blockchain for even greater security and decentralization.

SL is a decentralized machine learning framework that combines the principles of blockchain technology with federated learning. Instead of using a central server to compile model updates as in standard FL, SL uses a peer-to-peer network that is managed by blockchain to guarantee member validity, data integrity, and security. SL trains models locally, and only parameter weights are transmitted on a network of numerous swarm devices. The integration of blockchain technology ensures secrecy and security, enabling effective collaboration among disparate entities. Transactions can only be performed by preauthorized parties through computationally efficient consensus mechanisms. SL eliminates the need for a central server, reducing the risk of single points of failure and centralized data breaches. Unlike FL, which ensures data privacy through aggregating initial local gradients, SL facilitates data sharing among registered customers via smart contracts, thus preserving data privacy. A node in SL must undergo registration, authentication, model retrieval, local training, gradient sharing, and finally, result aggregation using the Federated Average method [15].

SL enhances fault tolerance, reduces vulnerability to attacks, and supports scalability, making it ideal for applications requiring high data privacy and system robustness, such as healthcare, the automotive industry, financial services, smart cities, edge computing, IoT, and the metaverse. In healthcare, SL guarantees the preservation of data privacy by allowing hospitals and research institutions to train models collaboratively without sharing sensitive patient data [16]. In the industry, SL enables machines and system components to act as individual learning agents, allowing real-time decision-making and adjustments without central oversight. It aligns well with Industry 4.0 principles, supporting advanced manufacturing technologies requiring high levels of data integrity, flexibility, and automation [17], [18], [19], [20]. In financial services, SL can enhance fraud detection systems by learning transaction data between different entities without compromising client confidentiality [21]. In smart cities, SL can optimize traffic flow and public transport management by allowing multiple sensors and nodes to learn and adapt to real-time traffic conditions. SL supports data sovereignty and auditability, ensuring compliance with data protection regulations. It also offers innovation and competitive advantage, allowing faster time to market and customization[22].

HAN et al. [23] sought to bridge the gap between the theoretical aspects of SL and its practical application, providing empirical evidence through experiments carried out on three public datasets. Their findings have evidenced that SL is supposed to be suitable for most application scenarios, no matter whether the dataset is balanced, polluted, or biased over irrelevant features. However, challenges remain, such as backdoor attacks against SL, managing blockchain integration complexity, and dealing with computational overhead.

1.1   Paper objectives and contribution

The considerable advantages offered by SL require a detailed examination to understand its current research landscape and practical applications, as well as to pinpoint areas requiring further improvement. To this end, this SL survey aims to investigate its capabilities within decentralized learning environments. Our objectives are to assess its practical implementation, identify both technical and operational challenges, and highlight potential avenues for future

innovations. Furthermore, the survey seeks to explore forward-looking developments, such as the integration of advanced cryptographic techniques to enhance security and the adaptation of SL to support emerging technologies such as edge computing and the IoT.

This effort will consolidate existing knowledge, clarify research gaps, and outline strategic directions to expand the adoption of SL. As a resource, this survey will be invaluable for scholars, researchers, and practitioners. By improving academic discourse and guiding practical implementations, it aims to pave the way for a broader application and optimization of SL in various industries, thus expanding its impact and utility.
To sum up, the main contribution of this paper can be presented as follows:

- We present the first survey paper in the field of swarm learning (SL). To the best of our knowledge, this literature review is the first review on SL.

- We provide a comprehensive overview of the existing literature on Swarm learning and its current applications to give readers a complete picture of this new and promising research direction.

- We studied and analyzed the current applications of SL. We categorized them into healthcare, transportation, industry, robotic systems, smart homes, financial services, multimedia IoT, fake news detection, and Metaverse.

- We present an in-depth analysis of the current limitations and challenges facing SL. We explore how these issues impact their development and deployment. Additionally, we discuss potential future directions to improve SL technologies and applications. We suggest paths for advancement and areas ripe for further research to enhance the effectiveness and applicability of SL technologies.

The road map of this paper, as shown in Fig.1 is outlined as follows: Section 2 provides an introduction to swarm learning and its fundamental concepts and components. Sections 3 and 4 explore the applications of swarm learning and its associated challenges, respectively. Section 5 highlights potential directions for future research in SL. The paper is concluded in Section 6.

1.2 Paper Selection

We conducted a comprehensive search in six databases, namely IEEE, PubMed, Science Direct, Scopus, Springer, and Web of Science. Specifically, we retrieved 25 papers from IEEE, 10 from PubMed, 116 from Science Direct, 72 from Scopus, 28 from Springer, and 43 from Web of Science. Subsequently, we meticulously screened these papers, focusing on those directly related to swarm learning, while excluding articles on swarm intelligence and swarm optimization. Following this screening process, we identified a total of 56 papers that met our inclusion criteria.

The number of research papers has increased each year, as shown in Fig. 2. Research on SL has steadily increased since its humble beginnings in 2020. By 2024, it experienced a significant increase, indicating the growing importance of SL in various fields. This surge highlights the growing interest of the academic community in exploring and maximizing the potential of this advanced technology. The surge in SL research is driven by advances in computational power, data availability, the proliferation of IoT devices, privacy-preserving AI techniques, and the emergence of complex problems such as healthcare, autonomous driving, and smart cities, which require scalable and decentralized learning methods.

1.3 Research Questions

1. What are Swarm Learning concepts, architecture, and components?
2. What is the difference between Swarm Learning and Federated Learning, Distributed FL/Decentralized Federated Learning, and Swarm Intelligence?
3. What are the applications of swarm learning?
4. What challenges do we see in the adoption and implementation of swarm learning in real-world applications?

2   Swarm Learning (SL)

SL is a decentralized machine learning framework that enables the training of the on-device model without the need to transfer raw data. In the SL model, the data is kept localized at the data owner's site, substantially reducing data traffic by avoiding the transmission of raw data [24]. Using blockchain technology, SL enhances privacy and security through the exchange of only the model parameters and weights, not the actual data itself. This approach incorporates smart contracts to manage the training and updating of the decentralized machine learning models using local user data, distinguishing it significantly from traditional centralized systems or even FL frameworks that rely on a central server
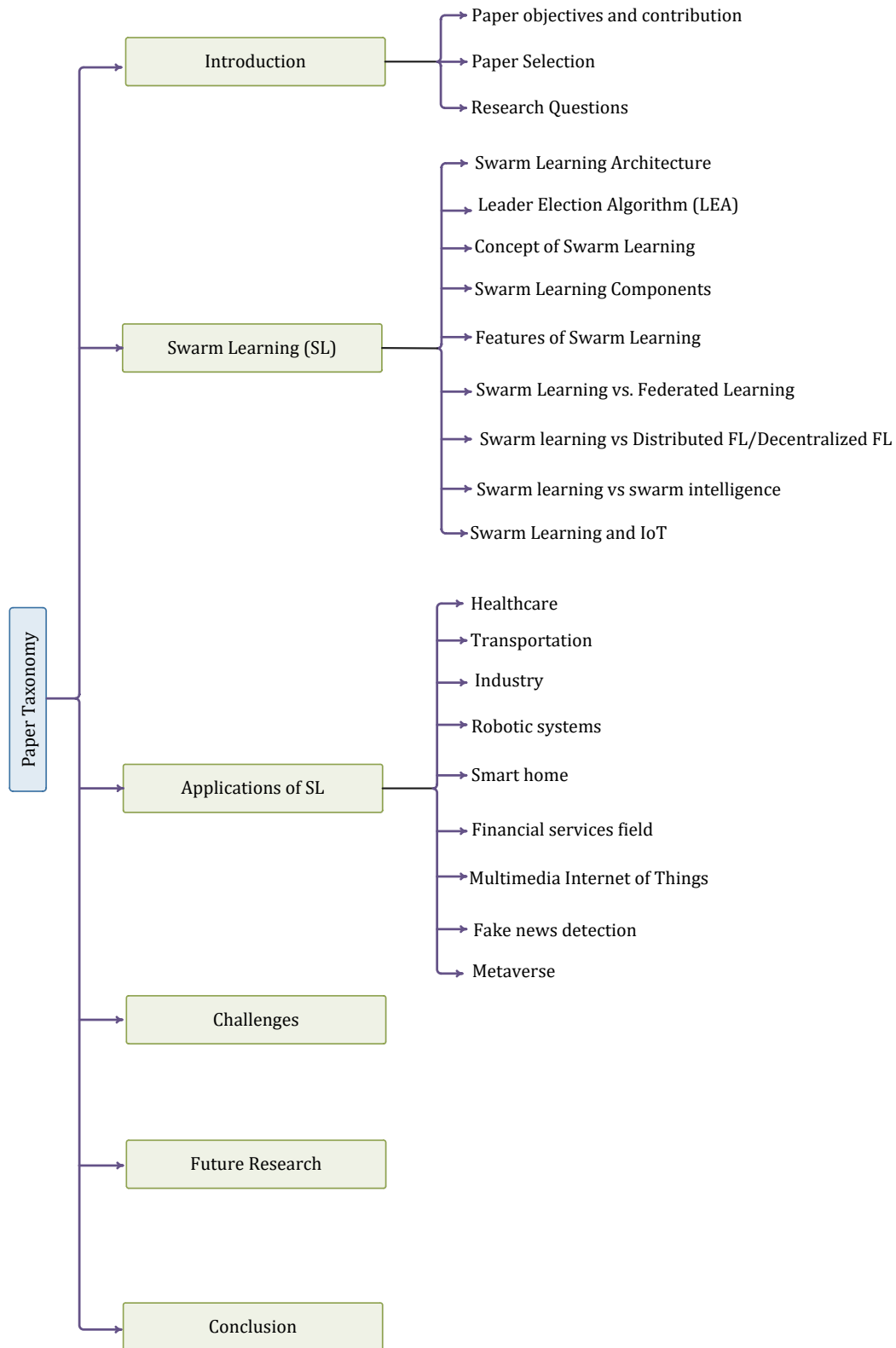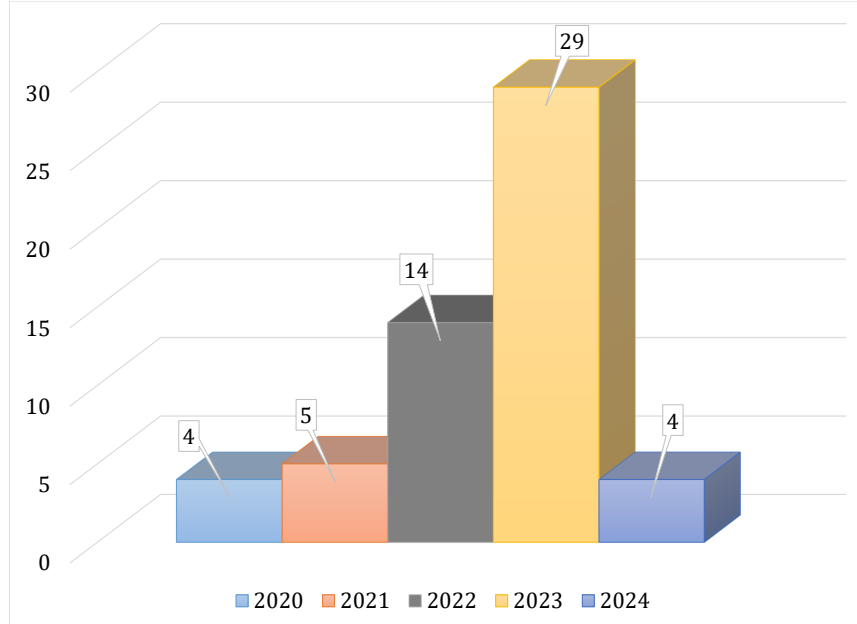
Figure 1: Paper Structure

Figure 2: Annual increase in the number of Swarm Learning research papers.

for aggregating model updates [21]. Additionally, SL incorporates advanced data privacy and security mechanisms, making it an ideal, flexible, and secure solution for content caching within contemporary network architectures [25].

SL employs a permissioned blockchain network and a decentralized hardware infrastructure to facilitate secure member onboarding, dynamic leader election, and efficient merging of model parameters. The system utilizes standardized AI engines within a distributed machine learning context to ensure secure and reliable operations. An SL library supports an iterative AI learning process that leverages decentralized data, adhering rigorously to the prevailing privacy and security standards [26]. This structured approach secures data and also streamlines the computational process across diverse network nodes.

2.1 Swarm Learning Architecture

The SL architecture encompasses two primary layers: the application layer and the infrastructure (or hardware) layer. The application layer includes the Machine Learning (ML) platform, blockchain, and the Swarm Learning Library (SLL). The hardware layer consists of data sources and models relevant to specific domains, such as datasets related to missions or geographic locations [4].

The SL system consists of two components: Swarm edge nodes and Swarm network (blockchain) [24]. With blockchain technology, SL has the following characteristics and advantages: (1) storing vast amounts of data locally; (2) reducing data traffic by not requiring the exchange of original data; (3) not requiring a secure central network; (3) offering high-level data security and shielding the model from attacks; and (5) allowing all members to merge parameters with equal rights [26].

Fig. 3 [6],[16], [27] depicts the architecture of the swarm learning system. There are several swarm edge nodes (let us say, M nodes), and each node Ci uses local private data Di, i = 1, 2, 3,..., M, to train its model Li after downloading an initial model from the network. Then, every node Ci distributes its model parameters throughout the network. These nodes are recognized, permitted, and registered with a smart contract in a peer-to-peer blockchain network to safeguard network security. Each node Ci has an opportunity to be chosen as a temporary leading node C for model aggregation in a training cycle t. When the local model Li is trained to satisfy predetermined synchronization requirements (such as a predetermined training batch), several chosen nodes will disclose their model parameters to a storm API. As a

result, each chosen node will get the global model parameters from the leading node C, which will then use a weighted average approach to aggregate them into a global model G [6].
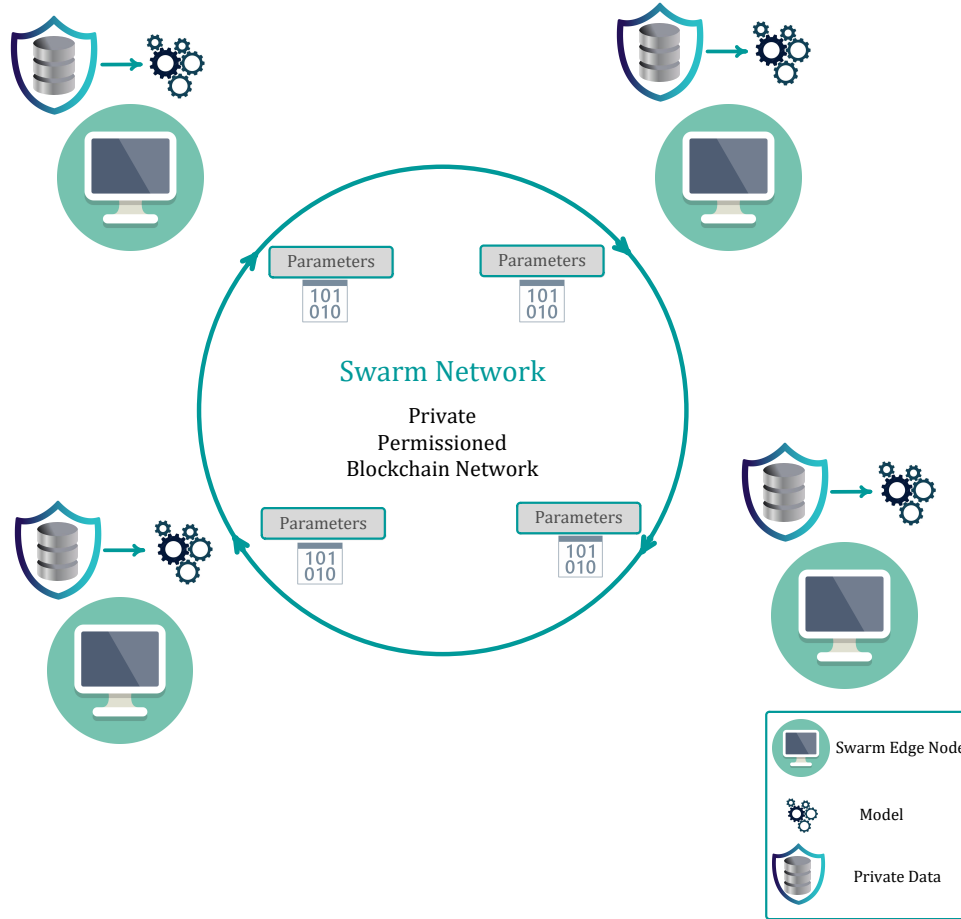

Figure 3: Swarm learning system architecture

The Swarm network diagram shows how edge nodes are set up to exchange parameters to learn, with blockchain technology serving as a facilitator. Private data is used at each node in combination with models provided by the Swarm network, guaranteeing a decentralized and secure method of collaborative learning [16]. To take part in model training, Swarm edge nodes must register via the blockchain's smart contract. After registering, every node uniformly downloads the first global model from the blockchain and trains the local model using its local data. Swarm edge nodes upload the local model parameters of the training to the leader via the Swarm network. The smart contract on the blockchain selects the Swarm edge node leader in real-time. The leader will average the collected local model parameters. To continue local model training, each Swarm edge node will download the aggregate model from the Swarm network until the aggregation model meets the requirements of the trained aggregation model. If not, the leader in a block generates the aggregation model [24].

The workflow for updating the model in SL, as shown in Fig.4 [28], consists of two primary stages. Initially, individual organizations trained their local models and updated them using their own SL nodes. These updates are then consolidated on their respective permissioned blockchains. In the subsequent stage, organizations use a network of multiple blockchains to further refine their local models and synchronize the global model's state. This approach of sharing models across various blockchains fosters a more decentralized SL process and mitigates security risks from external entities [28].

In SL, model sharing is seen as a data-transfer process among participating blockchains. The challenge lies in creating a method for blockchain data interplay that remains consistent and secure and is adaptable to various blockchain types without altering the core operations. The diversity in blockchain structures and consensus protocols used by different organizations adds to the complexity of enabling interblockchain interactions. Traditional methods of cross-chain
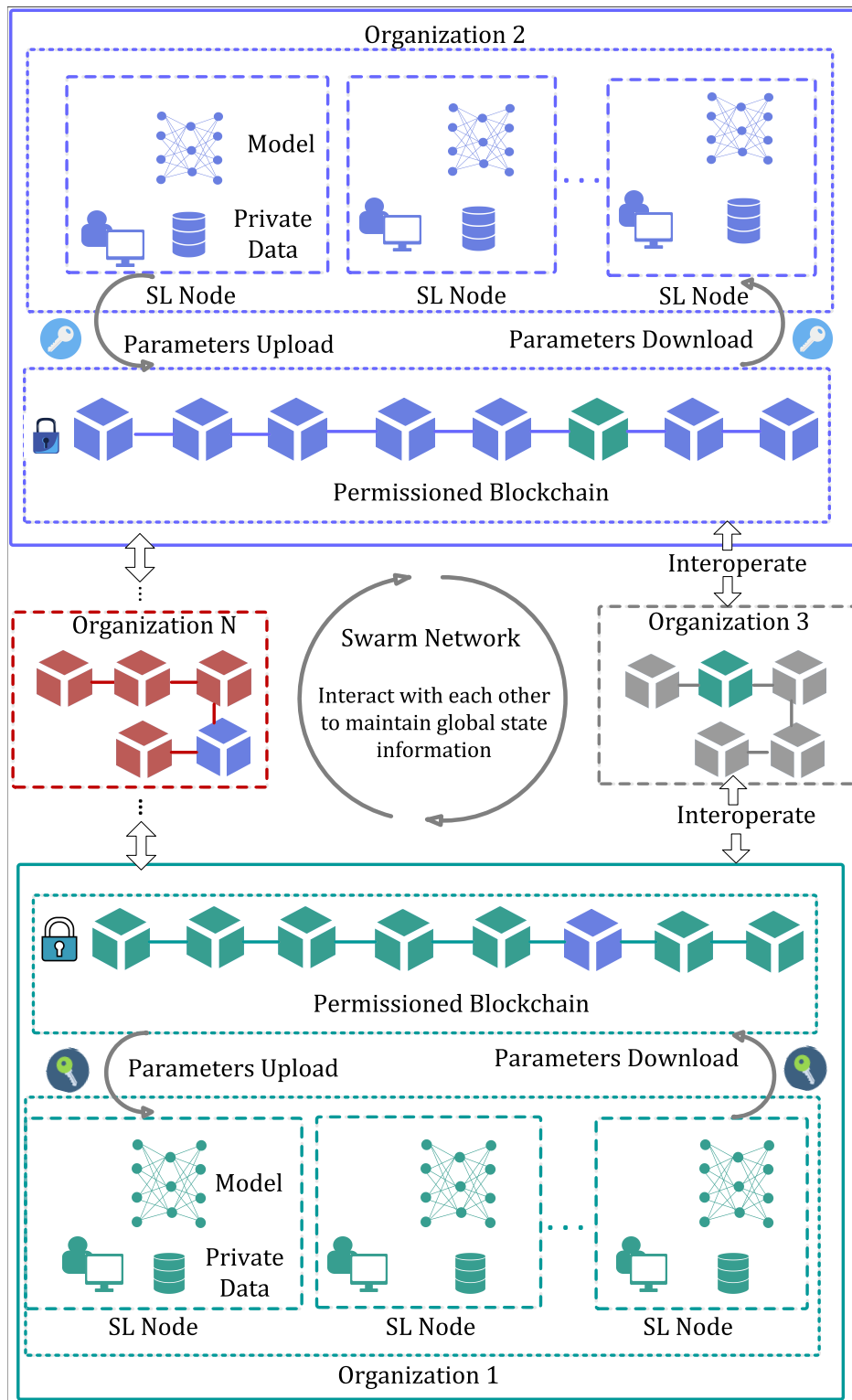
Figure 4: Workflow of SL with multiple permissioned blockchains. The chains of different colors belong to different participating organizations

communication, which often rely on a third-party trust entity, contradict the decentralized nature of SL and are therefore not suitable. Solutions such as the Cosmos architecture, which relies on a central hub for blockchain interoperability, also fall short of the ideal decentralized approach required for SL [28].

2.2 Leader Election Algorithm (LEA)

In SL, the fairness and performance of the network are greatly affected by the leader election process. Swarm edge nodes in SL are best placed on instances with plenty of bandwidth and processing power to handle the demands of decentralized decision-making. However, the unfairness of the leader election mechanism could cause nodes to use excessive amounts of bandwidth, which would result in inefficiencies and possibly bottlenecks. Participants may be unhappy with this discrepancy because they believe it is unfair and because nodes with higher data traffic may be more easily targeted by attackers[23]

The current LEA speculated to be a Proof of Stake (PoS), relies on leadership election on nodes' stakes or account balances. The authors in [23] recommended switching from PoS to a Proof of Work (PoW) model, in which nodes compete to solve cryptographic puzzles and leadership is established by meeting predetermined hash value requirements. By equating the likelihood of becoming a leader based on processing power, this technique seeks to guarantee a more fair distribution of network load among nodes. Future efforts will focus on collaborating with Hewlett Packard Enterprise (HPE) to enhance the fairness and effectiveness of LEA in SL.

2.3 Concept of Swarm Learning

ML, in theory, can be carried out locally if enough data and computing equipment are available. The data and computation existed at different, disconnected locations (Fig. 5 (A) [16]). In cloud-based computation, data are transported centrally (Fig. 5 (B)[16]) so that centralized computing can be used to perform machine learning. It greatly improves the amount of data available for training, and thereby improves machine learning outcomes. However, there are some disadvantages, such as increased data traffic and duplication, as well as problems with data privacy and security. In FL, parameter settings are managed by a central parameter server, while data remain with the data owner/contributor, and computing is performed at the location of local data storage and availability. Dedicated parameter servers are in charge of gathering and dispersing local learning in FL (Fig. 5 (C) [16]). Alternatively, SL eliminates the need for a dedicated server, as shown in Fig. 5 (D).SL distributes the parameters over the swarm network and develops the models separately at each location using private data [16].

The integration of ML methods into the SL framework can increase training rates. SL's decentralized nature allows local data processing at edge nodes, reducing latency, and potentially speeding up the training process. It also leverages the computational power of multiple decentralized nodes, improving training speed. SL reduces communication overhead by distributing workloads across multiple nodes, reducing the need for frequent communication between nodes. The blockchain component in SL manages model updates securely and efficiently, minimizing delays. Dynamic leader elections optimize the training process by choosing the most capable nodes for crucial tasks. SL's approach to handling non-IID data across different nodes can enhance model robustness and accuracy faster than centralized approaches. SL's ability to operate on nodes with varying computational capacities allows for resource optimization[16].

However, integrating ML methods into SL can introduce complexities, making it difficult to analyze training rate improvements. Traditional machine learning methods can vary in architecture and complexity, affecting learning rates, convergence behaviors, and efficiencies. SL's decentralized nature and varying computational resources may affect efficiency and scalability. Blockchain technology for synchronization may introduce overhead, and adjusting ML methods to fit SL could complicate performance assessment. Empirical studies and benchmarking against traditional centralized and federated learning systems are needed to quantify the benefits of SL in real-world scenarios.

2.4 Swarm Learning Components

As shown in Fig. 6 [29], the SL framework consists of various nodes:

- **Swarm Learning (SL) node**: SL nodes run the core of SL, sharing learnings and incorporating insights.

- **Swarm Network (SN) node**: Using the Ethereum blockchain, the SN nodes communicate with each other to track training progress and save global state information about the model. Additionally, during initialization, every SL node registers with an SN node, and each SN node manages the training pipeline for its corresponding SL nodes. Note that the model parameters are not recorded by the blockchain; instead, it simply stores metadata such as the model state and the training progress.
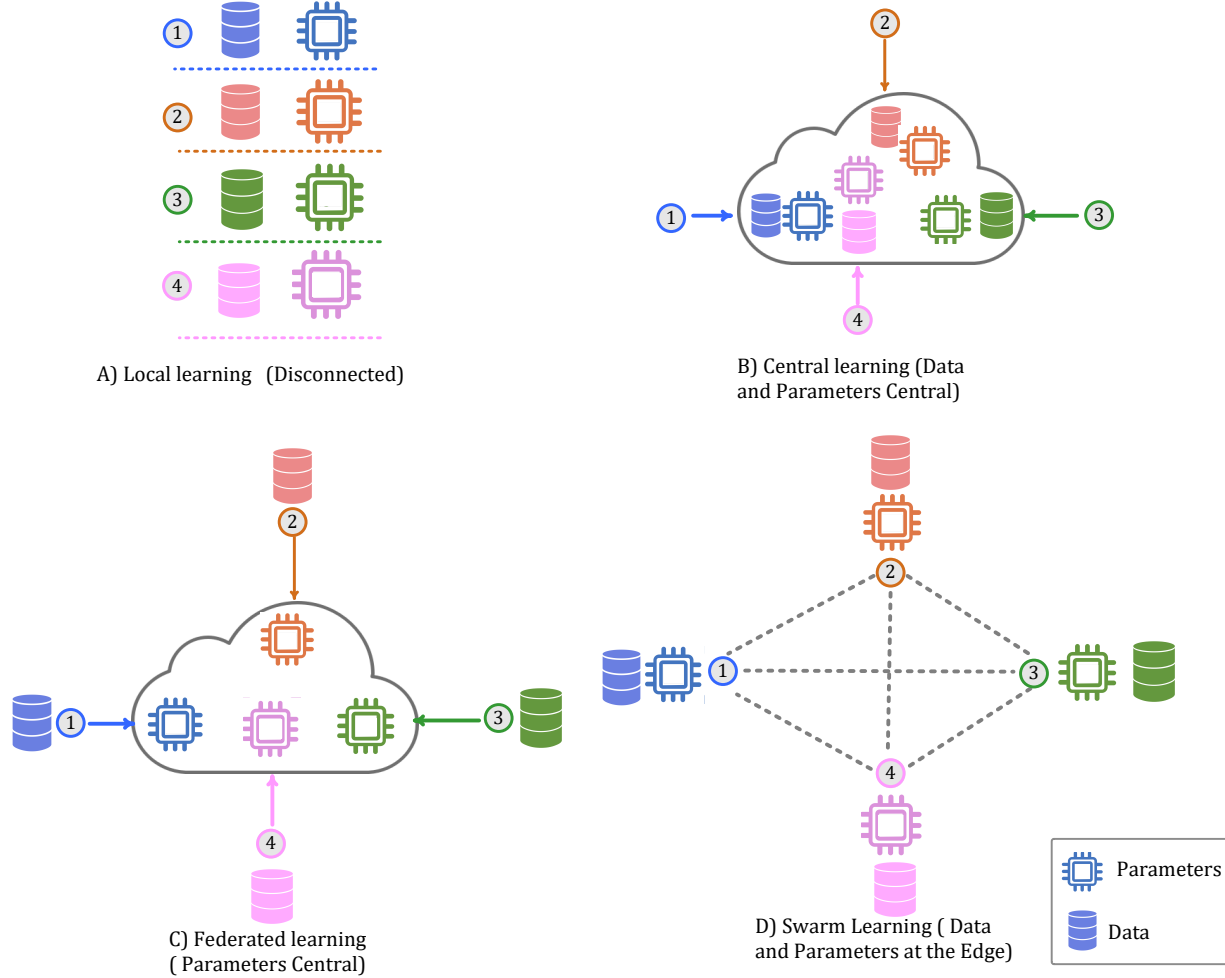
Figure 5: Comparative overview of learning models

- **Swarm Operator (SWOP) nodes**: SWOP nodes manage SL operations, performing tasks such as starting and stopping Swarm runs, building and upgrading ML containers, and sharing models for training.

- **Swarm Learning Command Interface (SWCI) nodes**: SWCI nodes monitor the framework and can connect to any SN node in a given framework.

- **Swarm Learning Management User Interface (SLM-UI)**: SLM-UI nodes are GUI management tools used to install the framework, deploy Swarm training, monitor progress, and track past runs[29].

- **SPIFFE SPIRE Server node**: SPIFFE SPIRE Server node ensures the SL framework's security. A SPIRE Agent Workload Attestor plugin is included in each SN or SL node, and it interacts with the SPIRE Server nodes to verify the identities of each node and to get and maintain an SPIFFE Verifiable Identity Document (SVID) [23].

- **License Server (LS) node** installs and manages the license to run the SL framework[23].

SL security and digital identity are handled by X.509 certificates, which can be generated by users or standard security software like SPIRE. SL components communicate using TCP/IP ports, and participating nodes must be able to access each other's ports[29].

2.5   Features of Swarm Learning

Swarm learning encompasses several distinct features that strengthen its application in decentralized settings:

Figure 6: Swarm learning Components

A. **Privacy Preservation:** SL keeps data at each node which minimizes the risk of privacy breaches and confidentiality.

B. **Decentralization:** SL reduces the risk of a single point of failure or data monopoly by eliminating the need for a central data storage or authority for model aggregation.

C. **Continuous Learning:** Models are continuously updated with new data available at each node, adapting to new conditions such as emerging diseases.

D. **Data Diversity and Volume:** SL handles larger and varied datasets from multiple nodes, enhancing model robustness and generalization.

E. **Collaborative Learning:** Nodes collaborate to train a shared model, benefiting from shared insights without actual data transfer, crucial to maintaining patient confidentiality.

2.6 Swarm Learning vs. Federated Learning

SL and FL are two distributed learning techniques that provide aggregation of cooperative models from numerous participating nodes [30],[31]. Several training rounds will result in the generation of a global model. Furthermore, to guarantee equitable and safe model aggregation, these participating nodes are not required to disclose their proprietary datasets. However, there are two key distinctions between them [26], [32].

- Information transmission: In FL, participating nodes and the central server exchange local model parameters as well as global model updates. However, in SL, peer-to-peer networks based on blockchain technology and edge computing work together to ensure that participating nodes can transmit safely and fairly without the need for central server coordination [6], [33],[34], [35].

- With or without a central server: In FL, a central server is utilized to collect model parameters from involved nodes and employ model aggregation to generate a global model. On the other hand, SL does not make use of a central server. During each training cycle, every participating node has the opportunity to be randomly selected to serve as a temporary server to compile model modifications. [6]. Using a blockchain-based Swarm network for safe and decentralized parameter exchange and aggregation of the model, SL eliminates the need for a central server [26].

SL addresses several key issues in FL and provides many benefits in security, privacy, and scalability. SL can envision ways to develop more secure, private, and faster distributed machine learning applications from different domains.

To tackle the gradient leakage and data privacy issues in FL, Madni et al [15] developed a secure, collaborative, and decentralized framework for machine learning training by combining blockchain technology with SL. SL protects the privacy of the data and the secrecy of the model parameters without unattended accesses and guarantees data integrity, since it authenticates only trusted nodes and deploys blockchain mechanisms. Research has been conducted against common machine learning approaches for anomaly detection, where it is demonstrated that the SL method gives better precision than current methods and addresses gradient leakage, which is the current major limiter of the FL.

In their two articles [36], [37], Xu et al. addressed issues such as data heterogeneity, security, and communication bottlenecks in FL by creating a strong edge learning framework for smart IoT devices. They presented a new technique called Communication-Efficient and Byzantine-Robust Distributed Swarm Learning (CB-DSL). This work is the first thorough theoretical examination of FL in conjunction with PSO (particle swarm optimization). It provides a closed-form formula to assess the projected convergence rate of CB-DSL, which makes it superior to traditional FL approaches such as Federated Averaging (FedAvg). It also offers a model divergence analysis to assess the possible advantages of adopting a globally shared dataset for enhancing learning outcomes in non-IId. situations.

2.7 Swarm learning vs Distributed FL/Decentralized FL

Decentralized FL and SL are two approaches to distributed machine learning that combine edge computing, blockchain technology, and peer-to-peer networking [38]. Decentralized FL eliminates the need for a central server, allowing for peer-to-peer communication and a more structured system, such as blockchain technology [39]. It also includes a consensus mechanism for updating the global model [40]. SL, developed by HPE Enterprise, integrates blockchain technology into its core operation, ensuring data integrity, node authenticity, and traceability. It also improves data privacy by keeping the data localized and maintaining security through cryptographic measures.

Decentralized FL involves various nodes working together to train a global model without a central coordinator, while Swarm Learning uses a leader election mechanism to aggregate updates and update the blockchain. Both approaches aim to decentralize the machine learning process and maintain data localization, but SL incorporates blockchain for security and dynamic network management. Both approaches are suitable for environments requiring high levels of data integrity and auditability. SL offers advantages such as enhanced privacy and security but may face challenges in privacy preservation and server-centric issues. Future research could explore empirical comparisons and develop hybrid models that combine the strengths of both SL and FL.

Beltrán et al.[12] explored the evolution of Decentralized Federated Learning (DFL) compared to Centralized Federated Learning (CFL), highlighting its benefits like improved fault tolerance and scalability. They compared DFL frameworks and their implementation in various applications, including healthcare, Industry 4.0, mobile services, military uses, and vehicular networks. Hallaji et al.[41] explored the security and privacy of DFL, highlighting its robustness and potential threats. They emphasized the need for comprehensive security analyses and ongoing research to mitigate inherent

risks in DFL systems. The integration of blockchain technology with decentralized federated learning (DFL) has been surveyed by Zhang et al.[11], [42], highlighting its operational workflow and applications in the IoT and Internet of Vehicles (IoV) domains. It discusses challenges like communication overhead and system complexity, recommending further research.

The choice between DFL and SL depends on the application's specific requirements, such as security, trust requirements, operational complexity, regulatory compliance, scalability, flexibility, real-time performance, data privacy, and cost implications. SL is ideal for fields like healthcare and finance, where data breaches or tampering could have severe consequences. DFL is suitable for scenarios where operational complexity and resource availability are concerns. SL is more suitable for highly regulated environments and requires strict data provenance and audit trails. DFL offers better scalability and flexibility, while SL may offer enhanced security features. However, the implementation and maintenance of a blockchain for SL can be more costly.

2.8   Swarm learning vs swarm intelligence

Swarm intelligence is a branch of artificial intelligence that uses the principles of basic agent behavior research to provide algorithms for scheduling, routing, and optimization issues. Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO), and Ant Colony Optimization (ACO) are examples of swarm intelligence algorithms. In contrast, SL is a subset of machine learning that focuses on distributed and dedicated learning without sharing raw data. SL emphasizes decentralized and collaborative machine learning in a privacy-preserving manner, while swarm intelligence focuses on problem solving and process optimization, drawing natural influences from a variety of systems.

Although SL and Swarm Intelligence have related names and are inspired by natural swarm behaviors, which may be confusing, it is important to compare them because, in computational and system design settings, they serve distinct purposes and operate on different principles within computational and system design contexts. Exploring the intersections and differences between SL and swarm intelligence can lead to the development of hybrid approaches that leverage the strengths of both. By comparing SL and swarm intelligence, researchers can identify new application areas that may benefit from either approach or a combination of both, aiding in educational and research development. Ultimately, comparing SL and swarm intelligence enhances the deployment of these technologies effectively across various domains.

SL provides an innovative set of effective solutions to the difficulties of conventional optimization algorithms in swarm intelligence. By addressing these issues, Swarm Learning overcomes the limitations of traditional optimization algorithms in swarm intelligence and also opens new possibilities for solving complex, dynamic, and large-scale optimization problems in a secure, efficient, and privacy-preserving manner.

The Bacterial Foraging Optimization (BFO) algorithm, introduced by Kevin M. Passino in 2002, is a nature-inspired optimization technique based on E. coli's natural foraging behavior. It has been applied in various fields, including engineering, control systems, and optimization problems. However, BFO has limitations depending on the problem's nature and implementation details, and its performance may not be ideal in all cases. Gan and Xiao [43] introduced swarm learning strategies to improve convergence accuracy and prevent premature convergence in BFO. This includes cooperative communication with the global best bacteria and competitive learning mechanisms, improving optimal solutions and swarm diversity, and addressing standard BFO deficiencies.

Bolshakov et al. [44] have developed a deep reinforcement learning algorithm called Deep Reinforcement Ant Colony Optimization (DRACO), inspired by traditional ant colony optimization and designed for cooperative homogeneous swarm learning. DRACO aims to shape collective behavior in decentralized systems of independent agents, offering an alternative to centralized learning. The algorithm's advantages include natural parallelization, solving collective tasks beyond the reach of single agents, increased reliability, faster environmental exploration, and economic and energy efficiency.

2.9   Swarm Learning and IoT

In conventional cloud-based structures, IoT devices send data to central servers for analysis. This approach can lead to potential bottlenecks, compromise data privacy during transmission, and also increase latency. SL, on the other hand, facilitates local data processing either on the device itself or on proximate edge servers, thereby decreasing the necessity to transmit sensitive data over the network and improving response times. SL enhances data privacy and security by keeping data localized and using blockchain technology for secure data sharing. This method ensures that sensitive data remain within the local environment, complying with data protection regulations such as GDPR. SL enables IoT devices to continuously learn and adapt in real-time, providing real-time insights and real-time updates. The distributed nature of SL provides excellent fault tolerance, making it suitable for IoT applications such as healthcare monitoring
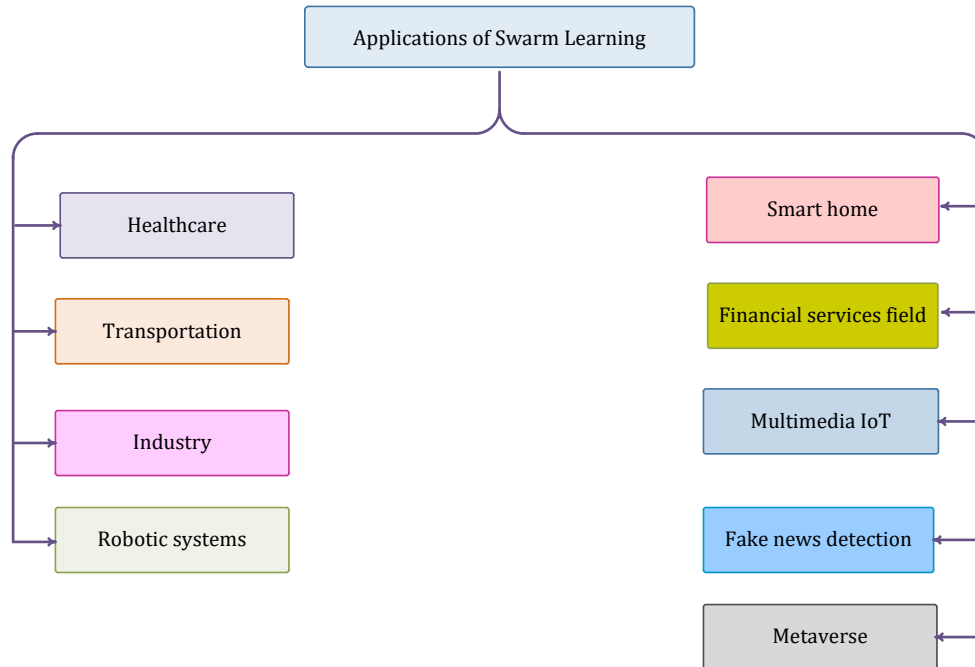
Figure 7: Swarm learning applications

systems and industrial automation. It scales well without relying on a central server, making it suitable for sprawling IoT networks. Implementing SL improves IoT networks' efficiency, security, and privacy compliance, making them better suited to handle vast amounts of data. The next section will explore more into the applications of swarm learning in IoT.

3   Applications of SL

SL is used in many fields, such as healthcare, autonomous vehicle systems, environmental monitoring, and robotics, as shown in Fig.7, to improve diagnostic accuracy, traffic flow, and safety. SL enables data aggregation without compromising privacy, allows communication and learning from experiences, and encourages cooperative robots for complex tasks. Its potential to revolutionize distributed systems and information processing is significant. The following subsections discuss the applications of SL in the reviewed papers.

3.1   Healthcare

Modern hospitals collect substantial volumes of private patient information electronically. These data are extremely private and secret because they pertain to both national security and individual privacy. The exchange of medical data between institutions is restricted by legal and privacy concerns, which impact the effectiveness of AI models trained on small datasets. While distributed deep learning reduces communication and computing costs by making optimal use of scattered data, it also poses privacy problems [24],[45]. SL enables local machine learning model training using data from multiple health nodes, such as hospitals. To maintain data privacy, the trained model parameters are then exchanged, combined, and dispersed among nodes without the requirement of a central collecting entity. By using blockchain, SL ensures data security and confidentiality [45].

As shown in Fig.8[46], the SLN plays a central role by using its unique digital identifier to train local models with private data and contribute to a collective global model. The SNN, pivotal for consensus within the blockchain, manages communication between the SLN and PBN, overseeing the training process, and maintaining the model's status. Lastly, the permissioned blockchain network underpins the model-sharing aspect of swarm learning, safeguarding the security and confidentiality of the process, and facilitating effective collaboration between the SLNs.

SL has demonstrated better performance in healthcare applications, such as COVID-19 profiles and chest X-ray images, allowing ongoing learning and enhancement across many data sources while closely respecting privacy laws such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act
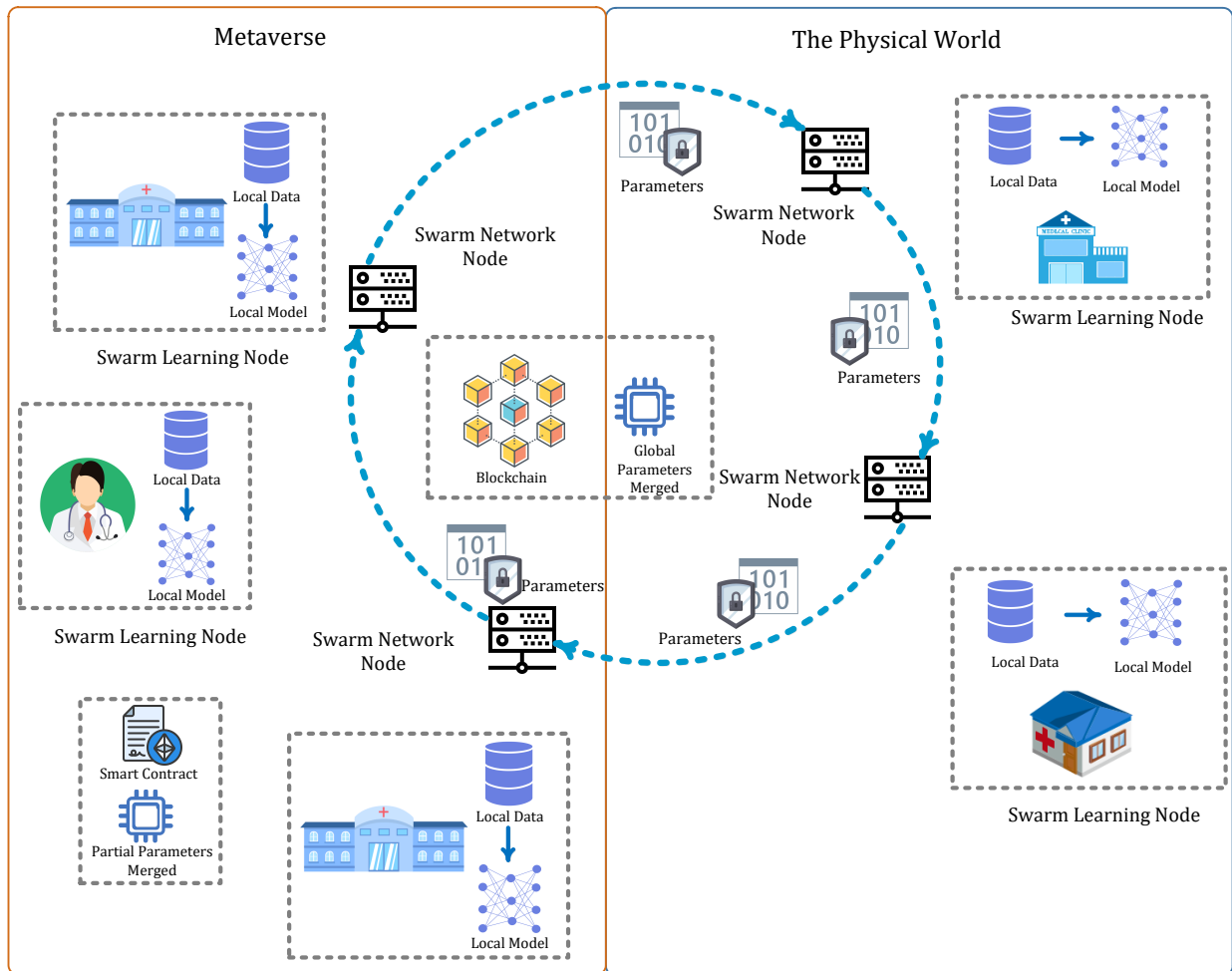
Figure 8: The framework of metaverse swarm learning, which enables cross-domain cooperation between metaverse and the physical world via blockchain

(HIPAA). It offers opportunities for the development of cooperative research and diagnostics across hospitals and research institutions networks and is flexible enough to fit a variety of medical data environments. For example, German university hospitals are using SL to evaluate COVID-19 patient data and create AI-based algorithms for the detection of novel biomarkers. SL will develop into a crucial tool for collaborative healthcare research and precision treatment [24],[45],[47].

For example, when hospitals use SL to manage COVID-19 data, they first gather encrypted and anonymized patient data, including symptoms and treatments. Every hospital sets up a separate SL node for safe local data processing. By eliminating raw data exchange, these nodes preserve data privacy by locally training models and sharing just the model parameters over a blockchain. These parameters are then combined by a blockchain consensus method to update and synchronize the global model across all nodes. Real-time deployment of this continuously improving model enables more effective diagnosis and treatment plans. SL improves predictive models by integrating diverse datasets from multiple nodes, improving accuracy and treatment efficacy. It prioritizes privacy and security by keeping sensitive patient data on-premises, reducing reliance on central repositories. SL also increases efficiency in hospitals by implementing personalized treatment plans. It is highly scalable, allowing easy integration of new nodes without significant infrastructure changes.

Warnat-Herresthal et al. in their novel study [16] use SL to train AI models on large datasets of histopathology images of more than 5,000 patients. SL was demonstrated for disease classifier development using distributed data from COVID-19, tuberculosis, leukemia, and lung pathologies, using over 16,400 blood transcriptomes. The study shows

SL's effectiveness in predicting molecular alterations in colorectal cancer, demonstrating its potential for enhancing medical imaging analysis without centralized data collection.

Fan et al. [26] was the first to examine the fairness problem in SL as it relates to healthcare, mainly in duties related to the class of skin lesions. They evaluated the fairness of the SL model for medical applications, comparing performance and fairness with the single, centralized, and SL models. The results show that SL can achieve better performance than single-institution training and does not amplify biases. However, the study acknowledges the high complexity of SL implementation due to the complex configurations of the blockchain network.

To overcome the difficulties presented by non-independent and identically distributed (non-IID) data in decentralized machine learning, notably in clinical contexts, Wang et al. [48] introduced a generative augmentation framework called SL-GAN, which combines a GAN in a swarm learning network to augment non-IID data into IID data. The non-IID problem is directly addressed for the first time in the context of SL in this paper, which is emphasized as a significant advancement in decentralized clinical machine learning research. The authors suggested improving synthetic data quality by introducing differential privacy and studying synthetic data privacy.

DeMed, a decentralized privacy-preserving system for medical image processing that uses blockchain technology, was proposed by Aggarwal et al. [49]. The approach aggregates data into a classifier using smart contracts after using self-supervised learning to create low-dimensional representations of medical images. This paradigm seeks to address security and resilience concerns in decentralized learning systems, with a particular focus on preventing malicious or unintentional data alterations. The efficacy of the system is demonstrated by independent medical picture classification tasks, such as chest X-rays and pathological data.

By integrating swarm learning with homomorphic encryption. These papers [24], [50] addressed a significant gap in distributed machine learning privacy-preserving techniques. Swarm learning participants can securely share model updates without disclosing sensitive data by incorporating homomorphic encryption. To maintain participant privacy, the authors devised a partial decryption algorithm that only required a fraction of the private key to allow participants to decrypt aggregated model information locally. This significantly advances the creation of machine learning applications in domains where privacy is a concern. They recommended handling offline participants, guarding against model poisoning, and maximizing encryption trade-offs as areas of future research.

Gao et al.[8] proposed a unique strategy for SL that gathers local knowledge from each center to overcome the forgetting of global knowledge during local training. The proposed methodology demonstrates how utilizing data from several centers can enhance medical picture segmentation while preserving data privacy and resolving skew problems with non-IID data. The Label Skew-Aware Loss (LaSA) is introduced to address label skew, preserving global label information during local training. LaSA maximizes the forecast for the most likely class determined by the global model. Feature Skew-Aware Regularization (FeSA) is used to align local feature distributions with the global model, mitigating the effects of feature skew caused by different imaging techniques or demography.

Yuan et al. [51] developed a cooperative deep neural network (DNN) partitioning system to accelerate disease diagnosis in multi-access edge computing (MEC) networks. They used Swarm Reinforcement Learning (SRL) to tackle the optimization problem of DNN partitioning and offloading and blockchain technology to address challenges such as limited resources and dynamic network environments. The algorithm allows agents to learn from local data and generate judicious offloading actions.

A study by Saldanha et al. [33] used SL to identify molecular biomarkers in gastric cancer from pathological images. They focused on microsatellite instability (MSI) and Epstein-Barr virus (EBV) status. Patients cohorts from the UK, USA, Switzerland, and Germany are included in their study. Every dataset is kept apart from the others. However, the study was constrained by uneven label classifications and the small number of biomarkers examined. Future research must use a larger number of biomarkers and larger and more diverse cohorts. To further enhance model performance and interpretability, the authors recommended investigating attention-based deep learning techniques.

Pan et al.[52] made a significant contribution to the field of drug development. The study presented a "Nanonitrator," a nitrate nanoparticle made of 3000 chitosan, sodium nitrate, and vitamin C as its main constituents. It was produced utilizing the microencapsulation technique. The purpose of this innovative nanoparticle is to improve nitrate's long-circulating delivery capability, extending its effects on the body's duration and potency without sacrificing safety. The authors described a novel method that uses a combination drug prediction system driven by SL technology to improve the bioavailability and protective effects of inorganic nitrate.

To predict molecular changes directly from hematoxylin and eosin (H&E)-stained pathology slides of colorectal cancer, the study by Saldanha et al. [34] uses SL to train AI models on large datasets of histopathology images from over 5,000 patients. The study shows the effectiveness of SL in predicting the BRAF mutational status and microsatellite instability, demonstrating its potential to improve medical imaging analysis without centralized data collection or control.

A unique methodology based on SL was presented by Zhang et al. [46] for the safe and equitable sharing of AI models in metaverse healthcare. The framework addresses security, fairness, and data quality issues, improving model accuracy and reliability. A novel parameter merging approach is devised to maximize local models of SL nodes using lower-quality data. A permission blockchain is used to incentivize high-quality data resources.

Mohammed et al. [53] developed a system using machine learning and SL to diagnose diseases from nail images. The system uses transfer learning models, InceptionV3 and VGG16, with an accuracy rate of 80%. The decentralized approach eliminates trust and uses blockchain technology for parameter merging. Despite limited training data, the system achieves an accuracy comparable to or better than centralized models.

The problem of using vast amounts of medical data for cancer research, particularly breast cancer, while adhering to privacy rules was the main focus of the study by Shashank et al. [54]. The primary contribution lies in showcasing SL, as a productive, privacy-preserving approach to improve clinical research through the analysis of varied datasets from various sources. They used 1,300 histochemical pictures of breast cancer tumors and follow-up records to analyze diverse datasets, demonstrating how SL can enhance clinical research, improve machine learning models, and maintain data privacy without compromising quality.

By integrating user feedback into AI model training, Purkayastha et al.[55] introduced a comprehensive approach that enables a more reliable and efficient collaboration between radiologists and AI. The system uses few-shot learning and SL, allowing continuous retraining of AI models based on active learning strategies. The platform presents new capabilities for human-AI partnerships, such as SL and few-shot learning methods. These techniques enable AI models built on active learning algorithms to be continuously retrained. Through the use of tailored model changes and collective knowledge, this approach facilitates more accurate and repeatable radiological assessments.

Shriyan et al. [56] introduced a novel method to detect cataracts, which is one of the most common eye conditions in the modern world, using SL. The authors highlighted the benefits of SL over conventional FL and centralized learning, emphasizing its effectiveness in the healthcare industry, especially when data privacy is crucial. Hospitals can improve early cataract detection by working together to create a global model while maintaining data privacy through the use of SL. The method advocates for a scalable paradigm that might include more nodes for higher data diversity and also proposes possible applications in identifying other retinal illnesses.

Table 1 summarizes the main contributions of those articles.

3.2 Transportation

Innovations in communication and computing technologies have significantly advanced the Internet-of-Vehicles (IoV). IoV is crucial to improving traffic management, emergency responses, flow control, and efficiency in Intelligent Transportation Systems (ITS). FL and Federated Deep Learning (FDL) have been introduced to address privacy issues in IoV [57],[58]. Despite the benefits of SL, there are drawbacks to using SL for collaborative Vehicle Trajectory Prediction (VTP). For example, the need for global communication across a large-scale network results in significant communication overhead, and the cost of blockchain increases with the number of participants, making SL less effective for large networks [57].

A framework that allows Vehicle Users (VUs) to cooperatively train and aggregate models without the requirement of a central coordinator was suggested by Lin et al. in [59]. An important consideration in the IoV environment is the mobility of VUs, which is taken into account in the proposed cooperative SL architecture. The authors create an incentive system based on an iterative double auction to entice VUs to participate in the SL process. An incentive mechanism and real-time models are included for dynamic vehicle environments. The authors developed an optimization problem that maximizes social welfare while achieving market equilibrium.

A novel SL approach for edge IoT contexts, communication-efficient, and Byzantine-robust distributed swarm learning (CB-DSL). To solve issues like data heterogeneity, communication constraints, and security concerns, CB-DSL integrates biological intelligence and AI. To strengthen the local model and the aggregation mechanism within the Direction Decide as a Service (DDaaS) scheme, they used a three-layer service architecture to transfer traffic data and control instructions, boosting forecast accuracy and real-time signal light switching management. The CB-DSL framework is validated using real-world healthcare datasets and simulation experiments with SUMO (Simulation of Urban MObility) to demonstrate its effectiveness in reducing traffic congestion compared to other existing methods.

IoV-SFDL (Internet of Vehicles-Swarm Federated Deep Learning) is a unique framework that was presented by Wang et al.[58]. It combines SL into the FDL framework and is specifically tailored for the IoV scenario. The goal of this framework is to overcome the drawbacks of FDL in IoV, including significant communication overhead, risks to data privacy, and difficulties brought on by vehicle movement, erratic communication, and dynamic settings. The system

Table 1: Swarm Learning in Healthcare

Ref	Application	Contributions	Methodology	Used Datasets	Key Findings	Future Work
[16]	Medical imaging	Demonstrated the potential of SL for enhancing medical imaging analysis.	SL for large-scale pathology image analysis	Tuberculosis, leukemia, COVID-19, and lung pathologies	SL enhanced medical imaging analysis by facilitating multi-centric collaboration and maintaining data privacy	Exploring additional medical fields where large, diverse datasets are crucial, possibly extending the decentralized model to more global collaboration.
[26]	Skin disease	Examined the fairness problem in SL	SL in skin lesion classification	Skin lesions	Investigated the fairness aspect of SL, showing robustness to heterogeneous data distributions and maintaining fairness without degrading performance	Future studies to improve model performance within the SL framework, focusing on managing model fairness and designing bias mitigation strategies for SL
[48]	Clinical settings	Overcame the difficulties presented by non-IID data in decentralized ML.	SL-GAN for non-IID data	Tuberculosis, Leukemia, and COVID-19 datasets	Addressed challenges posed by non-IID data in decentralized machine learning, specifically in clinical environments	Continued research to optimize decentralized clinical ML research, potentially exploring new algorithms and integration methods
[49]	Medical image analysis	A privacy-preserving decentralized framework for medical image analysis using blockchain technology.	Distributing a pre-trained Masked AutoEncoder (MAE) as a feature extractor and aggregating trained weights through smart contracts on the blockchain	Chest X-rays and pathological data	Developed a decentralized framework for medical image analysis, leveraging self-supervised learning and blockchain for privacy-preserving model training	Expanding the framework to include more complex medical imaging tasks, potentially increasing the variety of diseases that can be diagnosed using the system
[24], [50]	Privacy-preserving techniques	Including homomorphic encryption into SL.	Enhancing the Paillier homomorphic encryption using the Chinese Remainder Theorem for efficient operations and integrating a blockchain-based SL architecture for decentralized model aggregation through FedAvg	MNIST dataset	Significantly advanced machine learning applications in privacy-sensitive areas by allowing secure model updates sharing without revealing sensitive data	Enhancing defenses against model poisoning, optimizing encryption trade-offs, and handling offline participants
[8]	Medical imaging	Overcoming forgetting global knowledge during local training. Solves skew issues with Non-IID data.	Local knowledge assembly, LaSA loss, FeSA regularization	FeTS, M&Ms, MSProsMRI, MMWHS datasets	Enhanced medical image segmentation by handling Non-IID data issues, preserving data privacy	Further application to systems with unidirectional input constraints and expanding to other medical imaging tasks
[51]	Disease diagnosis	A cooperative DNN partitioning system for accelerating disease diagnosis in MEC networks.	Swarm Reinforcement Learning (SRL) in MEC networks	VGG16, AlexNet, ResNet18, NiN	Accelerated DNN-based disease diagnosis through cooperative DNN partitioning and offloading, minimizing service latency	Real-world applicability validation in clinical settings with specific constraints.
[33]	Molecular biomarker prediction	Predicting molecular biomarkers in gastric cancer from pathological images.	training MSI and EBV prediction models in individual merged cohorts and SL trained, using statistical analysis to assess prediction accuracy and explainability through pathologist-reviewed visualizations	Datasets from Bern, Leeds, TUM Cohort, TCGA	Improved prediction of molecular biomarkers in gastric cancer using multicentric data without compromising privacy	Expansion to include more biomarkers and larger datasets, exploring attention-based DL methods for improved model performance
[52]	Drug development	SL-based combination drug prediction system that identified vitamin C as the drug of choice to be combined with nitrate	AI-driven drug discovery, "Nanonitrator" nanoparticles	DPN, DDN, DTN from DrugBank, ChEMBL, UniProt	Enhanced bioavailability and therapeutic effects of inorganic nitrate for prolonged efficacy and safety	Not explicitly mentioned, but likely involve further clinical trials and detailed pharmacokinetic studies
[34]	Medical imaging	Predict molecular alterations from H&E-stained slides of colorectal cancer	A retrospective analysis of colorectal cancer patient images from five cohorts, using SL to train and validate ML models for predicting molecular features like MSI and BRAF mutations	Datasets from Northern Ireland, Germany, UK, TCGA, YCR BCIP	Demonstrated feasibility and effectiveness of SL in training AI models to predict molecular alterations in colorectal cancer using large, multicentric datasets	Expanding the SL application to other oncology areas and enhancing scalability and applicability of AI technologies in routine diagnostics.
[46]	Metaverse healthcare	Safe and equitable sharing of AI models in metaverse healthcare. A novel parameter merging approach for SL nodes.	SL nodes that train local models using private data, Swarm Network Nodes (SNN) for blockchain communication and monitoring, and a Permissioned Blockchain Network (PBN) for secure collaboration	COVID-19 dataset, PAMAP dataset	Improved accuracy and reliability of healthcare AI models in metaverse by ensuring security, fairness, and data quality distribution	Enhancing security and fairness in model-sharing processes through further integration of decentralized technologies
[53]	Disease diagnosis	Diagnose diseases from nail images.	Integrating three components: SL Node for managing insights, SNN for blockchain operations, and ML Node for training models using pre-trained bases	Four nail disease classification datasets on Google Cloud Drive	Achieved high diagnostic accuracy with a decentralized approach using transfer learning models, maintaining patient privacy	Expansion to other types of medical data and further enhancement of model training processes to maintain high accuracy with limited data
[54]	Cancer research	Using vast amounts of medical data for cancer research while adhering to privacy rules.	SL for training decentralized cancer diagnosis model across two nodes simulating different medical data sources. Data from the WDBC, WPBC, and BreakHis datasets, featuring both tumor characteristics and images, were split between nodes to reflect diverse medical scenarios	BreakHis, WDBC, WPBC	Utilized large volumes of medical data for cancer research while adhering to privacy norms showing how SL facilitates decentralized learning	Extending the decentralized model training to improve oncology research outcomes, leveraging larger and more diverse datasets
[55]	Radiology	A new capability for Human-AI partnerships.	SL with user feedback in AI model training	WDBC, WPBC, BreakHis	Introduced a system that incorporates user feedback in AI training, promoting personalized and efficient radiological assessments	Further development of Human-AI partnership capabilities, optimizing the interaction between radiologists and AI models
[56]	Eye disease detection	A novel method for detecting cataracts.	Pre-processing and data splitting, model training with the VGG-19 architecture, and Swarm Learning integration.	ODIR dataset, a collection of retinal images	Highlighted the advantages of SL over traditional centralized and federated learning systems in detecting cataracts	Expanding the model to include more diseases and larger networks for richer data diversity

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is more effective for IoV situations where the model training convergence speed is accelerated through the use of an algorithm in the framework to anticipate the credibility of weights.

The directed acyclic graph (DAG)-based Swarm Learning (DSL) framework was created by Huang et al.[60] to address challenges such as unreliable communications and vulnerability to malicious attacks in IoV. DSL combined blockchain, Edge Computing (EC), and FL technologies to provide asynchronous model training and data sharing in IoV. The authors created a Dynamic Vehicle Association (DVA) algorithm based on DSL to handle vehicle movement and enhance model training efficiency by maximizing the links between Vehicle Nodes (VNs) and Road Side Units (RSUs). The DSL framework uses a method to detect malicious attacks, ensuring security and resilience. It also introduces a reward mechanism to encourage honest participation in model training, promoting a collaborative and trustworthy learning environment.

Hou et al. [57] proposed Hierarchical Swarm Learning (HierSL), a novel edge-assisted framework for Vehicle Trajectory Prediction (VTP). HierSL is proposed to improve efficiency and security in the collaborative learning process, particularly for large-scale edge-assisted IoV systems. HierSL reduces global communications reliance and blockchain costs. Tests are carried out on an actual NGSIM US-101 data set, and the outcomes demonstrate that the suggested approach outperforms vanilla Swarm Learning and as well as centralized learning.

Yin et al. [22] proposed a Multi-Region Asynchronous Swarm Learning (MASL) framework. MASL is a hierarchical blockchain-powered framework for large-scale data exchange in IoV. The blockchain, EC, and FL technologies were all merged by MASL to ensure the anonymity and security of the sharing process. Secure asynchronous model training and identity authentication have been accomplished by coordinating the intra-regional (IR) and cross-regional (CR) sharing and the non-IID data issues between regions. Furthermore, the DAG-enabled MASL is a fully asynchronous system that is capable of responding to anomalous vehicles on the IoVs.

Liu et al. [61] introduced a 6G-driven urban traffic congestion mitigation solution called DDaaS. DDaaS includes a model layer for data collection, parameter training, and congestion value prediction, a Swarm Network (SN) layer for safe parameter transmission, and a decision-making layer for signal light switching. Based on SUMO, simulation trials demonstrate that DDaaS can reduce traffic congestion and achieve accurate prediction.

Autonomous driving technology has advanced significantly, but privacy concerns arise due to the use of sensors and cameras. Mishra et al. [62] proposed an SL-based training approach to address these concerns. By sharing model learnings across nodes, SL protects sensitive information and reduces privacy breaches. SL presents a promising solution to create effective and respectful autonomous driving systems. This approach offers performance comparable to traditional methods and outperforms other distributed machine learning techniques like FL. Table 2 shows the main contributions of these articles.

3.3 Industry

The Industrial Internet of Things (IIoT) is being developed using technologies such as IoT, big data and digital twin (DT). Combining IIoT with AI algorithms can improve productivity and interoperability, offering solutions for advanced manufacturing systems. However, the DT technique faces challenges in capturing dynamic industrial environments due to its data-driven nature and security and privacy concerns[64]. SL is revolutionizing manufacturing by providing real-time intelligent agents that improve operational efficiency by streamlining manufacturing lines, dynamically allocating resources, and instantly resolving problems. This approach allows for production line optimization, dynamic resource allocation, and real-time problem solutions without centralized control. SL is ideal for companies aiming to use Industry 4.0 and smart manufacturing, creating more resilient and intelligent factories for the future [65],[20]. However, there is limited research on integrating SL with IIoT. Reliability issues in industrial systems are crucial, especially in emergencies. Industrial environments are complex and subject to high temperatures and noise, making them more complex than normal environments. With automation, competition for limited communications resources increases the unreliability of IIoT systems[64].

Pongfai et al.[17] developed a Dragonfly Swarm Learning Process (D-SLP) algorithm for nonlinear feedback control systems, improving robustness, performance, and stability. The D-SLP controller demonstrated superior performance in simulations of a permanent magnet synchronous motor control system compared to other control methods. However, the study acknowledges limitations and suggests future work for unidirectional input constraints and input dead zones in systems.

Using a deterministic Q-Swarm Learning Process (Q-SLP) algorithm and SL principles, Pongfai et al.[18] created an enhanced control approach. This method optimizes proportional integral and derivative (PID) controller parameters, improving system performance, stability, and convergence. The approach improves convergence time and performance

Table 2: Swarm Learning in Transportation

Ref	Application	Contributions	Methodology	Used Datasets	Key Findings	Future Work
[59]	IoV	A new framework that allows VUs to cooperatively train and aggregate models without the requirement for a central coordinator. An optimization problem that maximizes social welfare while achieving market equilibrium.	Cooperative SL framework with an incentive mechanism based on the mobility of vehicle users	-	Proposes a more communication-efficient method than FL; enhances social welfare and dynamic adjustment to mobility	Develop the incentive mechanism to ensure fair participation and better model aggregation methods
[63]	Edge IoT	Communication-efficient and Byzantine-robust Distributed Swarm Learning (CB-DSL) combining AI with BI principles	Evaluating the model performance under both i.i.d. and non-i.i.d. conditions and in the presence of Byzantine attacks.	CIFAR-10 and MNIST datasets	Improves local model accuracy and decision-making in traffic management; addresses local optima issues	Validate the framework in real-world settings and address more inherent challenges in edge IoT environments
[58]	IoV	IoV-SFDL: Overcomes the drawbacks of FDL in IoV, including significant communication overhead, risks to data privacy, and challenges caused by vehicle movement, erratic communication, and dynamic settings	Integrates SL into Federated Deep Learning framework	Next-Generation Simulation (NGSIM) dataset	Addresses communication overhead, improves model convergence speed in IoV contexts	Explore additional IoV-specific challenges and expand the framework to more dynamic scenarios
[60]	IoV	Improve data sharing and model training in the context of IoV	Directed Acyclic Graph-based SL (DSL) combining edge computing, FL, and blockchain	Traffic Signs Preprocessed dataset based on GTSRB	Enhances data sharing and model training; Introduces dynamic vehicle association and malicious attack detection	Develop more robust mechanisms for attack detection and introduce more adaptive algorithms for vehicle mobility
[57]	Vehicle Trajectory Prediction (VTP) in IoV	A novel edge-assisted framework for VTP	Hierarchical SL with a two-layer learning framework	NGSIM US-101 dataset	Reduces global communication reliance and blockchain costs; improves security in large-scale IoV systems	Optimize synchronization steps and system topology for better accuracy and efficiency
[22]	IoV	A secure, efficient framework for large-scale data sharing in IoVs	Multi-Region Asynchronous Swarm Learning (MASL) with hierarchical blockchain for parallel execution	Traffic Signs Pre-processed dataset based on GTSRB	Addresses scalability, security, and data heterogeneity; maintains user data privacy in large-scale data sharing	Improve the asynchronous training methods and expand blockchain integration for better data privacy and security
[61]	ITS	Direction Decide as a Service (DDaaS) to Reduce Traffic Congestion in 6G-Driven ITS. A traffic simulation and congestion prediction experiment using SUMO in Beijing, China.	Direction Decide as a Service (DDaaS) with a novel three-layer architecture incorporating SL	-	Facilitates the orderly transmission of traffic data and control instructions; improves traffic management and reduces congestion	Enhance the traffic control algorithm for more adaptive and timely decisions; expand to more complex ITS scenarios
[62]	Autonomous Driving Systems	Training autonomous driving systems	SL-based training method for privacy preservation and performance enhancement	Kitti 3d dataset	Claims superior privacy preservation and potentially better performance over traditional methods	Expand research to compare with more distributed machine learning techniques and validate in practical autonomous driving contexts

by addressing shortcomings in conventional techniques. Simulations showed superior performance and convergence over traditional SLP, improved particle swarm optimization (IPSO), and the whale optimization algorithm (WOA).

Pongfai and other authors created an adaptive SLP method in a different work [66]to create the best PID controller possible for multiple-input/multiple-output (MIMO) systems. The approach dynamically updates online weights depending on system failures, improving PID parameter autotuning performance, stability, and resilience. The authors evaluated the algorithm against conventional techniques using a two-wheel inverted pendulum system as a case study. The method could be investigated to approximate discrete-time responses, predict behavior, and observe systems.

Sun et al.[19] proposed a new diagnostic framework for bearing faults in rotating machinery, addressing data privacy concerns and insufficient labeled data in factories. The framework uses convolutional neural networks and adversarial domain networks to train local diagnostic models without sharing data. Sun et al. in another paper [20] proposed a framework using SL to diagnose faults in multiple components of the machinery, addressing data privacy and insufficient data. The framework uses local diagnosis models like AlexNet and the Chebyshev filter, enhancing efficiency and accuracy.

Xiang et al.[64] presented a ground-breaking architecture for IIoT that is enhanced by DT technology and powered by credibility-weighted SL. Their method tries to solve the privacy risks and significant communications costs. With the aid of DT, they developed a DRL technique to simultaneously optimize energy consumption and IIoT system reliability.

Table 3: Swarm Learning in Industry

Ref	Application	Contributions	Methodology	Used Datasets	Key Findings	Future Work
[17]	Nonlinear control systems	A Dragonfly Swarm Learning Process (D-SLP) algorithm for nonlinear feedback control systems	Blendsing dragonfly algorithm behaviors with SL protocols to adaptively tune control parameters amidst system variations; A two-layer blockchain framework to ensure secure and private intra-regional and cross-regional data sharing among vehicles and base stations	-	Superior control performance in nonlinear systems compared to conventional methods	Explore application to systems with specific constraints like PAM
[18]	PID controller optimization	Use a deterministic Q-SLP algorithm to optimize and improve the PID parameter's autotuning process	A Deterministic Q-SLP Algorithm for optimizing PID controllers, combining swarm and learning to refine control parameters KP, KI, and KD, enhancing system response and stability	CPC system	Improved convergence and performance optimization over traditional methods	Not specified
[19]	Diagnostic frameworks for rotating machinery	A new diagnostic framework for bearing faults in rotating machinery	Integrates adversarial domain networks with CNNs	CRWU, HITsz, XJTU-SY, and SCU	Increased efficiency and accuracy in fault diagnosis without compromising data privacy	Not specified
[64]	Industrial Internet of Things (IIoT)	A revolutionary architecture for IIoT powered by credibility-weighted SL and improved by DT technology	Digital Twin technology with credibility-weighted SL	real-world MNIST dataset	Enhancing IIoT system reliability and reducing energy consumption	Further address practical concerns in IIoT for operational efficiency
[65]	Reconfigurable robotic assembly cells	A method for optimizing the layout of reconfigurable robotic assembly cells in manufacturing environments	Multi-agent cooperative swarm learning with digital twin	-	Improved layout optimization and operational efficiency in manufacturing	Enhance the framework to adapt to rapid changes in manufacturing demands
[67]	Data management in engine lifecycle	A blockchain-based data management method to ensure engine data integrity	Utilizing blockchain for secure data interactions, and employs a trusted application (BCAPP) for data processing and validation	NASA open dataset	Enhanced data integrity and security throughout the engine's lifecycle	Optimize multi-party collaborative learning and data usage

To address issues with operational efficiency and sustainability, they also developed and solved an optimization problem in the recommended DT architecture to optimize system reliability and minimize energy usage.

Wang et al.[65] have introduced a novel approach that utilizes cooperative multi-agent SL and DT to optimize robot assembly cells and thus can be adapted to any manufacturing environment. This model of interaction, where each element acts as an autonomous agent, permits these agents to respond instantaneously to issues of mechanical structure, networked software, and hardware integration. The approach considers each component as an agent, allowing them to interact dynamically to address mechanical structure, software, and hardware integration changes. The framework supports dynamic reconfiguration, ensuring efficient manufacturing systems in response to varying product demands and production cycles.

Luo and Zhang [67] have developed a blockchain-based data management method to ensure the integrity of the engine data, preventing tampering and deletion. The method uses SL to verify the integrity of engine test data and protect privacy. The integrated approach improves trustworthiness, supports collaborative learning, and optimizes data usage while protecting privacy.

Table 3 shows the main contributions of these articles.

3.4 Robotic systems

Learning processes can be significantly accelerated when multiple robots work together to form a swarm. Such entities could exchange learned information in a decentralized or centralized fashion. In SL, nodes in the network pool share locally learned models among themselves without the need for a central authority. When using SL in networked robotic applications, a collection of linked robots must be able to operate together or independently to complete tasks. Rangu and Nair [68], offered a method that uses mobile agents to execute SL on a group of robots and each learns a task. The learning process is distributed, with a mobile agent compiling and disseminating the models learned locally as it moves seamlessly across the network of both simulated and actual robots. The authors demonstrated the SL approach using a mixed group of both simulated and real robots, considering that assembling a swarm solely of real robots would be cost-prohibitive. The application of reinforcement learning at the local level to groups consisting of simulated, real, and combinations of these robots has proven the viability and efficiency of SL within a diverse network of robots.

3.5 Smart home

Edge Intelligence (EI) integrates edge computing and AI in smart homes, real-time video analysis, and precision agriculture. However, centralized machine learning models have limitations like data privacy breaches and communication overhead[69]

SL is transforming smart home ecosystems by enabling decentralized decision-making processes. This allows smart devices to communicate and learn from each other's experiences, optimizing energy consumption, security, and automation. Smart thermostats, lighting, and appliances can adjust settings based on occupants' habits, ensuring comfort and energy efficiency. Swarm learning also allows security networks to analyze data and adapt without human intervention.

Xu et al. [69] introduced a novel cooperative SL framework to overcome Central Machine Learning issues by leveraging decentralized SL for the prediction of thermal comfort. This approach reduces communication overhead and improves model performance by leveraging real data from all nodes within the edge computing network. The framework's effectiveness was demonstrated through an extensive empirical investigation using a Non-IID thermal comfort dataset.

Liu et al.[70] developed ADONIS, a framework for detecting abnormal behavior in IoT devices. It uses Swarm Learning, knowledge distillation, and human-computer interaction (HCI) to improve security and operational efficiency. The decentralized approach reduces central node failure risk and reduces latency and energy consumption. ADONIS can be applied to smart cities and IoVs, and its adaptability makes it suitable for various applications. Future research includes further enhancements and refinement of parameter aggregation methods.

3.6 Financial services field

By using decentralized networks for data analysis, decision-making, and risk management, SL is completely changing the financial services industry. Swarm learning's decentralized nature reshapes data-driven decisions in the complex financial landscape. Enhance investment recommendations and fraud detection rates while protecting against single points of failure. By using SL, financial organizations can modify their strategy in response to current market conditions and consumer trends. John et al.[21] used SL for credit scoring in Peer-to-Peer lending on a blockchain platform in the financial services industry, ensuring user data privacy and secure transactions. The decentralized model training and credit scoring process eliminate centralized data storage risks. Future work includes testing with real-time datasets and improving user experience.

3.7 Multimedia Internet of Things

By enabling the processing and dissemination of decentralized content in real-time in environments containing IoT devices, swarm learning is transforming the Multimedia IoT ecosystem. This method guarantees that content is personalized for each user, minimizes latency, and maximizes network capacity utilization. Additionally, processing data locally on devices improves security and privacy by lowering the possibility that private information will be hacked.

Zhang et al.[71] have improved the privacy and security of multimedia IoT devices using Radio Frequency Fingerprinting (RFF) for identity authentication. They integrated differential privacy, specifically the Gaussian mechanism, into SL to protect RFF data. They also proposed a novel node evaluation mechanism to prevent malicious nodes from affecting the model's accuracy and integrity. By guaranteeing the security of the underlying IoT devices through enhanced privacy protection in SL, the research paves the way for safe multimedia services.

3.8 Fake news detection

Social media has significantly impacted the distribution of information, but the lack of systematic management has led to the spread of fake news. Machine learning techniques like convolutional neural networks (CNN) and recurrent neural networks (RNN)can detect fake news, but centralized detection can violate user privacy. Decentralized methods like SL offer privacy-preserving learning on local data, reducing hacking risks and allowing users to maintain confidentiality without sharing data [72]. Dong et al.[72] developed Human-in-the-loop Based Swarm Learning (HBSL), a decentralized method for detecting fake news. HBSL uses SL and human-in-the-loop (HITL) techniques to detect fake news across nodes, ensuring user privacy. It incorporates user feedback, allowing models to be continuously updated. The method was validated using a benchmark dataset (LIAR), showing its superiority over existing methods.

Table 4: Swarm Learning Applications

Field	Ref	Application	Contributions	Methodology	Used Datasets	Key Findings	Future Work
Robotic systems	[68]	Networked robotic applications	A method that uses mobile agents to execute SL on a group of robots	Mobile agents executing SL on a group of robots; Each robot learns individually, and a mobile agent facilitates the aggregation and sharing of locally learned models across the swarm	-	Demonstrated viability and efficiency of SL in a mixed robot swarm; reinforced learning applied locally to enhance task completion	Not specified
Smart home	[69]	Edge intelligent computing networks	Cooperative SL framework with cyclic ring all reduce topology for thermal comfort prediction	utilizing stochastic gradient descent within a cyclic edge intelligent computing network.	Non-IID thermal comfort dataset	Demonstrates reduced communication overhead, enhanced data privacy, and improved model performance by leveraging data from all nodes without sharing it	Extend empirical investigations, optimize model performance and handle real-world applications' data distribution issues
	[70]	IoT, specifically abnormal behavior detection	ADONIS, a framework for detecting abnormal behavior in IoT devices	SL combined with knowledge distillation and HCI for anomaly detection in IoT devices	Traffic dataset	Enhanced security and operational efficiency in IoT networks by local data fusion and a lightweight model to accommodate resource-constrained environment	Further framework enhancement, increase communication efficiency, and refine parameter aggregation for non-IID data
Financial services field	[21]	Credit scoring	Credit scoring in Peer-to-Peer lending on a blockchain platform in the financial services industry	Lending platform on Web 3.0 that connects lenders and borrowers using blockchain technology to ensure secure, peer-to-peer transactions without intermediaries	Universal Bank dataset	Ensures data privacy and secure transactions, with model performance comparable to centralized approaches	Test model with dynamic datasets, explore other decentralized platforms (Solana, Hyperledger, Corda), and enhance user experience
Multimedia IoT	[71]	Multimedia IoT device security using RFF	Improved the privacy and security of multimedia IoT devices using RFF for identity authentication	Integration of differential privacy and a novel node evaluation mechanism in SL	RFF dataset	Enhancing privacy and security for IoT devices by protecting RFF data and making the system resilient against various cyber attacks	Future research could focus on extending these methodologies to broader IoT applications and further improving the robustness of the security measures
Fake news detection	[72]	Decentralized fake news detection	Human-in-the-loop-based swarm learning (HBSL), a decentralized method that incorporates user feedback for detecting fake news	The methodology involves local learning, collaborative model update and human feedback to enhance detection capabilities across the network through a cyclic process	LIAR dataset	Significantly improves the accuracy of fake news detection using local data and user feedback	Design detection models tailored to specific node features to enhance effectiveness
Metaverse	[73]	6G-Metaverse XR communication	SL-based secure configurable resource trading mechanism for reliable 6G-Metaverse XR communication.	A decentralized trading framework using SL for resource management in a 6G-Metaverse environment, facilitated by IRS and blockchain technology, and Federated Learning for privacy enhancement.	Custom dataset	Effective in reliable XR communication via decentralized management and smart contract-based resource trading	Investigate customization of SL for more fine-grained communication hardware resource management and scheduling

3.9 Metaverse

The Metaverse faces challenges in reliable extended reality (XR) data transmission due to a lack of incentives and untrust among users. To address these issues, a configurable secure resource trading mechanism based on swarm learning is proposed in [73]. This framework includes subchains for decentralized Intelligent Reflecting Surfaces (IRS) resource management and intelligent allocation, a smart contract-enabled scheme, and a decentralized federated learning-driven IRS allocation scheme. Experimental results demonstrate the effectiveness of this configurable SL-based resource trading for reliable XR communication.

Table 4 shows the main contributions of those articles.

4 Challenges

4.1 Non-IID Problem in SL

SL enables participants to register, train models, and exchange parameters through edge nodes, ensuring data sovereignty and confidentiality. However, SL performance is significantly affected by non-independent and identically distributed (Non-IID) data[48], which can lead to inconsistent model updates and degraded aggregate performance. When data is dispersed unevenly among various network nodes or participants, it is called the non-IID problem in SL. This implies

that distinct statistical characteristics, such as mean, variance, and data distribution patterns, may exist in the dataset at each node. Several factors, including variations in patient demographics, the type of medical equipment utilized, or even the particular focus or specialization of the medical institutes providing the data, might contribute to this heterogeneity in the data. Non-IID data problems include quantity, label, and feature skews. Feature skew and label skew are caused by differences in imaging protocols or demographics, leading to inconsistencies in annotations and Non-IID label distributions. Various strategies, including elastic weight consolidation and batch normalization, have been proposed to address feature, label, and quantity skew in classification tasks. However, these methods do not fully consider label skew, which could cause suboptimal performance[8], [74].

Two types of strategies are now being used to tackle the non-IID challenge: algorithm-based and data-based approaches. Algorithm-based methods align local models with global models, while data-based methods balance distribution but require a trusted central coordinator. Furthermore, with non-IID data, convergence problems may arise when utilizing Generative Adversarial Networks (GAN) for data augmentation[48].

To address the non-IID problem in SL, methods must be created that can either reduce the impact of data heterogeneity or take advantage of it to increase the global model's resilience and generalizability. Strategies such as advanced aggregation techniques, personalized models, and data augmentation can improve the robustness and generalizability of the global model[8]. Currently, effective solutions to address the non-IID problem in SL are yet to be established[48].

4.2 Fairness and bias in SL

Fairness and bias in machine learning models indicate how they could perform or reflect dominant groupings in the data in an unbalanced way. The impact of SL on model bias and fairness has not yet been fully assessed, even though fairness issues have been considered in the context of FL. In[26], the authors suggested comparing SL with centralized learning and subgroup-specific model training to investigate the fairness of SL in medical imaging tasks without the need for additional bias mitigation techniques. To provide insight into how SL might balance performance and fairness in healthcare applications, their study seeks to determine if SL's fairness features are more in line with centralized learning or subgroup-specific training.

4.3 Attacks on swarm learning

SL has the potential to handle distributed large-scale data better than FL, but it also faces significant security issues that require more scrutiny. In the stages of SL, as shown in Fig.9 [6], different attacks can occur: unreliable parties may compromise data during local training and before the locally trained metadata are secured on the blockchain, it might be vulnerable to various network attacks like Eclipse and DDoS. Furthermore, malicious participants could introduce harmful parameters during the merging process, potentially introducing backdoors into the global model. 1) Data poisoning might occur in the local training phase; 2) eclipse attacks could occur in the blockchain P2P network in the metadata upload phase; and 3) the global model could be hacked by poisoned parameters in the parameter aggregation phase [6].

4.3.1 Backdoor attacks against distributed swarm learning

Despite its privacy and decentralized training benefits, SL faces significant security threats, such as backdoor attacks, which need to be addressed to ensure the integrity and reliability of SL systems. Backdoor attacks in machine learning, especially SL, manipulate data and training processes to produce incorrect outputs. In SL, where multiple nodes collaborate, a backdoor attack could be particularly insidious. Moreover, the decentralized nature of SL makes detecting such attacks challenging due to the non-IID nature of real-world data. Addressing backdoor attacks requires technological solutions, robust security practices, and new collaborative learning approaches to ensure integrity and trustworthiness in decentralized machine learning environments[6],[35].

Chen et al.[6] conducted a study on security threats in SL using a pixel pattern backdoor attack method. Their research consists of a number of studies that evaluate the effectiveness of backdoor attacks in diverse scenarios utilizing a variety of datasets (MNIST, CIFAR-10, SVHN). These circumstances include varied network sizes, different data distributions (IID vs. non-IID), distinct attack targets (single vs. multitarget), and attack continuity policies (single-shot vs. multiple-shot). To reduce the effects of backdoor attacks, they also suggested a number of security strategies, including L2 regularization and the addition of noise. Experimental data verify the efficiency of these protections.

Yang et al.[35] identified a hybrid vulnerability in SL that uses backdoor and eclipse attacks to propagate backdoors secretly. They introduced a strategy called sample-specific eclipse (SSE) to target high data contribution nodes, reducing attack costs and accelerating backdoor propagation. The study investigates the use of distributed backdoor poisoning attacks in conjunction with Eclipse assaults for the first time, showing how they can be used together to allow backdoors
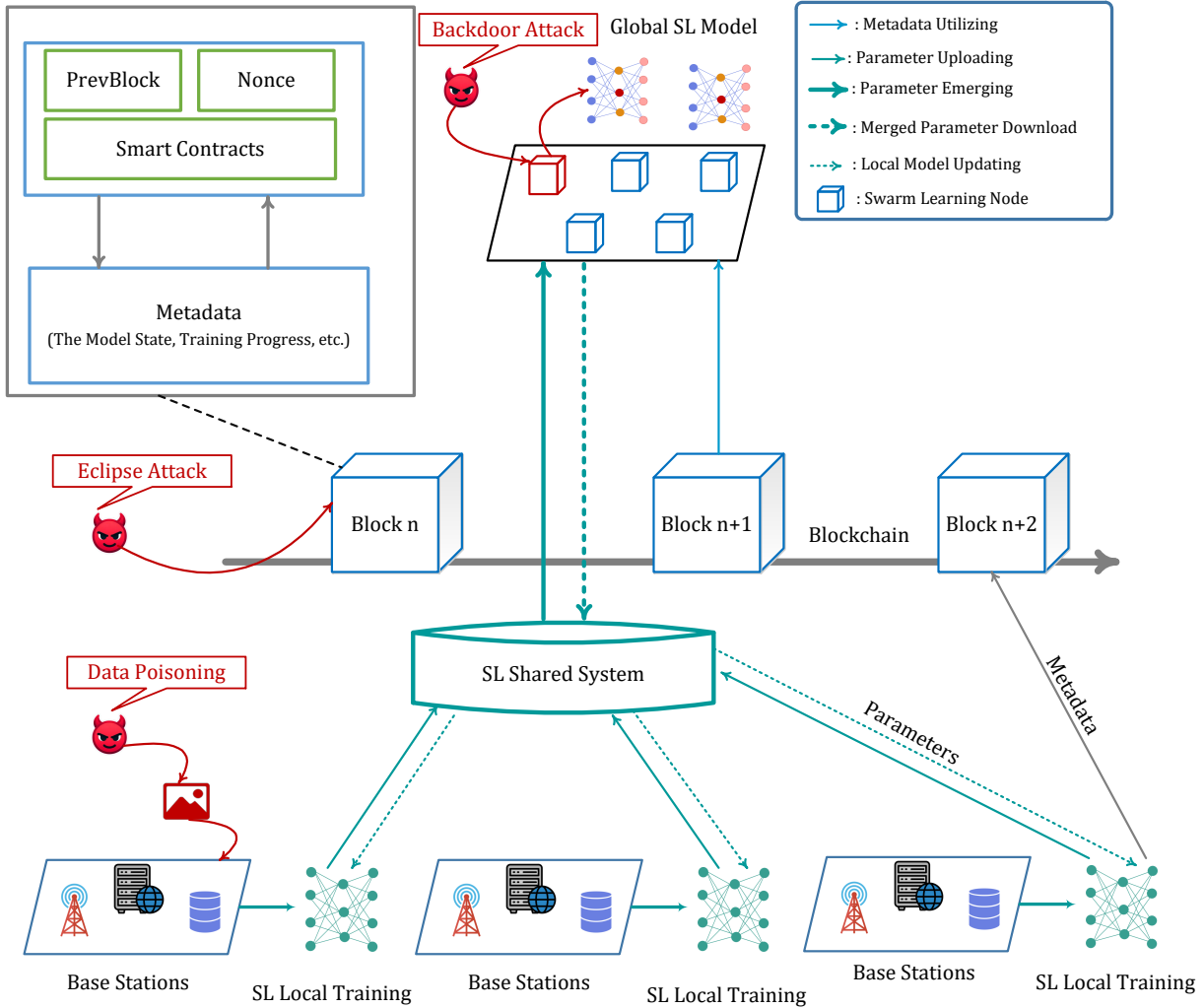
Figure 9: Attack on swarm learning

to spread covertly among innocent users on the SL network. Afterward, they suggested a fresh assault plan that concentrates on nodes that contribute a lot of data, speeding up the spread of backdoors and requiring fewer resources overall to be effective.

4.3.2 Poisoning attack

SL faces unique challenges from poisoning attacks. Poisoning can compromise the collective learning process, affecting model parameters and performance. The decentralized nature of SL complicates detection, as there is no central authority to monitor data quality or model updates. Therefore, robust decentralized consensus mechanisms are needed to detect and mitigate poisoned inputs [35], [71],[28]. Qi Y. et al.[28] developed strategies to prevent poisoning attacks and ensure the integrity and security of the SL process.

Rongxuan et al.[75] introduced a Zero Trust Architecture (ZTA)-based defense scheme for SL to combat poisoning attacks in decentralized learning environments. It identifies a unique vulnerability where a malicious 'header' node can compromise the model. The defense mechanism emphasizes continuous risk calculation and anomaly detection, allowing dynamic responses to threats. The scheme also uses Manhattan distance and accuracy differences to identify and mitigate risks from both the header and edge nodes. The effectiveness of the proposed defense strategy is demonstrated through systematic experiments, proving its practical applicability in real-world scenarios.

4.3.3   Eclipse attack

An Eclipse attack in SL involves an attacker controlling the network communication between nodes. This is particularly relevant in peer-to-peer networks where nodes share information and model updates without a centralized authority [35]. An attacker can isolate a target node or group of nodes by monopolizing their network connections, potentially introducing false data or model updates [76]. This could impact the integrity of the model and degrade performance. To protect against Eclipse attacks, robust peer discovery and management mechanisms should be implemented, including diverse peer connections, validating peer identities, and detecting network patterns that might indicate control of communication channels[35].

4.3.4   Inference attacks

Inference attacks aim to deduce sensitive information about the training data used by a model, such as recovering private or sensitive attributes. They can be used to determine if a specific data record was part of the training set, infer specific attributes or features of data instances, or attempt to reconstruct a model's parameters. Inference attacks focus on extracting information about the training data or model behavior, such as determining if specific data were used in training or guessing private attributes based on model outputs. Decentralized machine learning methods allow multiple nodes to collaboratively learn a shared model without exchanging local data, typically through blockchain technology [77]. Inference attacks exploit shared model updates or the final model to infer properties of the training data or identify unique characteristics of individual participants' datasets. To protect against inference attacks, advanced cryptographic and privacy-preserving techniques such as homomorphic encryption, secure multi-party computation, and differential privacy are employed. However, the balance between privacy protection and model performance is a critical challenge in SL[71].

4.3.5   Model inversion attacks

Model inversion attacks aim directly at reconstructing the inputs used to train the model, effectively reversing the model's computations to approximate or reveal the actual data. They often target models that provide detailed or confident predictions, which can inadvertently reveal information about the training data [78]. While inference attacks often derive indirect information about the data or its attributes, model inversion attacks engage in a more direct and complex effort to recreate the original training inputs themselves. In SL, where nodes collaborate to train a model without sharing their local datasets. The decentralized nature of SL allows each node to contribute to the model's learning by updating it based on local data. However, shared model updates or predictions can leak information, potentially inferring specific characteristics or reconstructing aspects of the original training data. To defend against model inversion attacks, strategies such as output perturbation, differential privacy mechanisms, access controls, and strict query limits can be implemented[71].

5   Future Research

SL addresses privacy and data integration issues, but research gaps exist, indicating potential areas for further exploration.

- **Security and Trust**: Although SL uses blockchain technology to ensure security and trust, more investigation is required to solve potential security flaws, such as sophisticated cyber threats and insider attacks. It is essential to have strong trust mechanisms and security measures specifically designed for SL networks. Swarm-FHE [79] offers a significant advancement in SL security by integrating fully homomorphic encryption and blockchain technology. This method ensures that collaborative model training is conducted without compromising data, even in the presence of compromised or malicious participants. Blockchain technology and lightweight homomorphic encryption are also combined in a privacy-preserving SL by Li et al. [44], which promotes model security, data privacy, and computational performance and offers a competitive substitute for FL in remote machine learning applications [80].

- **Dynamic Node Management**: Enhancing the robustness and dependability of SL systems may involve investigating dynamic techniques for node participation and incentive mechanisms to guarantee nodes' continued and productive engagement in the swarm network.

- **Optimizing Leader Election**: The leader election process in SL can lead to disproportionate bandwidth consumption, inefficiencies, and potential bottlenecks, causing dissatisfaction among participants and potentially compromising network security. To address these challenges, [23] suggested refining the leader election mechanism for more equitable network load distribution.

- **Scalability and Efficiency**: The ability of SL to expand across a growing number of nodes and a variety of data formats while maintaining efficiency and model performance should be investigated. Enhancing

model aggregation techniques and communication protocols could be the main areas of research to facilitate widespread implementations of SL.

- **Interoperability and Standards**: For SL to succeed, standards compliance and interoperability amongst various systems are essential. To solve issues with data format, protocols, and compliance, research could examine methods for SL to seamlessly integrate into existing IT systems. Qi et al.[28] developed a blockchain twin mechanism to improve the interoperability and efficiency of SL on different blockchains, introducing an incentive mechanism for active participation, thus improving the overall performance and security of the SL process.

- **Energy Efficiency**: Considering the possible magnitude of SL deployments, especially in the context of IoT, the development of power-saving learning algorithms is of the utmost importance. The emphasis of such research would be on minimizing the energy usage of devices involved in the SL process, a factor that is particularly critical for devices running on batteries or sensors located remotely.

- **Cross-domain Applications**: Investigating the potential use of SL in diverse sectors like healthcare, autonomous vehicles, smart cities, and manufacturing can be extremely advantageous. Each of these areas poses distinct challenges and demands, and customized SL approaches could result in significant advancements in the way these sectors employ decentralized learning.

- **Data Heterogeneity and Non-IID Data**: To efficiently tackle the non-IID issue in SL, forthcoming studies might concentrate on the creation of a hybrid model adaptation method that merges both algorithmic innovations and robust data management strategies. The goal of this method should be to reduce the effects of data heterogeneity and boost the performance and unification of the global model in a distributed environment.

- **Advanced-Data Augmentation Techniques**: Investigate the application of advanced generative models, like variational autoencoders (VAEs) or enhanced GANs, for the production of synthetic data samples. These samples can efficiently supplement sparse or imbalanced datasets across different nodes, thereby addressing the non-IID problem.

- **Ethical AI and Fairness**: As SL models become more widespread, it is crucial to ensure that these models do not perpetuate or exacerbate biases. Research could focus on developing fairness-sensitive algorithms that promote ethical AI practices within SL frameworks.

- **Resource Management**: As mentioned in[23], the impact of adding more Swarm coordinator nodes on resource overhead is negligible. However, the resource overhead increases linearly with the number of Swarm edge nodes added, indicating that scaling these nodes should be done with care. This observation provides valuable guidance and actionable recommendations for developers and researchers looking to apply SL effectively in real-world scenarios.

- **Integrating ML into SL**: The integration of ML methods into the SL framework can introduce challenges in analyzing the specific contributions of SL to training rate improvements. SL uses blockchain technology to synchronize model updates amongst nodes. Although confidentiality and integrity are guaranteed, the overhead resulting from blockchain operations (such as consensus processes and transaction validations) may outweigh the anticipated gains in training speed from concurrent decentralized training. Therefore, integrating ML methods into SL may complicate the assessment of training rate improvements. Empirical studies and benchmarking against traditional systems are needed to assess its benefits in real-world scenarios.

6 Conclusion

SL is a promising advancement in decentralized machine learning that enables efficient, secure, and privacy-preserving collaborative learning without central data storage. This review provides invaluable information on the advantages of SL and emphasizes how SL can facilitate safe, confidential, and effective collaborative machine learning across dispersed networks. Highlights the benefits of SL, such as improved data privacy, reduced risk of centralized breaches, and the ability to learn from diverse data sources without data transfer. SL has potential applications in healthcare, IoV, industry, etc. However, challenges like non-IID problems, fairness, bias, and vulnerability to attacks need to be addressed. Robust decentralized consensus mechanisms and advanced cryptographic techniques are essential for the integrity and privacy of SL. These research gaps offer a wide range of opportunities for researchers interested in advancing the field of decentralized machine learning.

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