Model-Centric Federated Machine Learning

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Traditional Federated Machine Learning follows a server-domincated cooperation paradigm which narrows the application scenarios of federated learning and decreases the enthusiasm of data holders to participate.

CCS Concepts: • **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

Introduction: Federated Learning [27].

Four roles in FL systems design: the data owners, the model users, the coordinators, the auditors.

1.1 Related Surveys

In recent years, federated learning has become a buzzword in various fields, leading to the emergence of numerous FL studies. These works can be classified into three primary categories: FL systems design, FL appllications and FL toolkits. Extensive surveys are available to summarized the advancement of federated learning, as shown in Table 1. The initial architectures and concepts for FL systems were summaried by Yang *et al.* [49]. They categorized FL into horizontal FL, vertical FL and federated transfer learning based on the distribution characteristics of data, which are written in IEEE Standard 3652.1-2020 [43, 48]. Following this, an increasing number of surveys have emerged focusing on enhancing FL system design [5, 21, 26, 27, 53]. From the algorithmic perspective, personlized FL [23, 45] aims to learn personlized models for each client to address the challenge of statistical heterogeneity [33]. Besides, the privacy-perserving computing platforms and model aggregation protocols for FL systems also been widely studied and sumaried by [11, 31, 32, 51]. Furthermore, many advanced FL architectures had been proposed, such as asynchronous [46], decentralized and blockchain-based FL frameworks [36, 38, 58]. Given that federated learning technologies enable collaboration among distributed participants in model training and decision-making, this capability holds great promise in a wide range of application scenarios. For instance, multiple geogrphically distributed medical insitutions can enhace medication recommendation, drug-drug interaction prediction and medical image analysis in a collaborative manner without exchanging any sensitive data [6, 37, 41, 47]. The massive real-time data generated by IoT devices in smart cities [39, 55], industries [8], vehicles [10] has also sparked interest in exploring how FL technology can be used to deliver more advanced services such as intrusion detection, anomaly detection, fraud detection and network load prediction [3, 4, 14].

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Table 1. Summary of existing FL surveys, SYS denotes FL Systems Design, APP denotes FL Applications, SDC denotes Server-Dominated Cooperation frameworks.

		Challenges					Contents		
Scenarios/Tasks	FL Surveys	Efficiency	Heterogeneity	Privacy	Incentive	Decentralized	SYS	APP	SDC
General	Yang *et al.* [49]	✓	✓	✓	✓	✓	✓	✓	✓
	Li *et al.* 2020 [27]	✓	✓	✓		✓	✓	✓	✓
	Zhang 2021*et al.* [53]	✓	✓	✓			✓	✓	✓
	Gupta *et al.* [15]	✓	✓	✓		✓	✓	✓	✓
	Xu *et al.* [46]	✓	✓	✓		✓	✓	✓	✓
	Li *et al.* 2021 [26]	✓	✓	✓	✓	✓	✓	✓	✓
	El *et al.* [11]			✓		✓	✓		✓
	Kulkarni *et al.* [23]	✓	✓				✓		✓
	Liu *et al.*[31]	✓		✓		✓	✓		✓
	Tan *et al.* [45]		✓				✓		✓
	Zhu *et al.* 2021 [57]		✓				✓		✓
	Ma *et al.* [33]	✓	✓	✓			✓		✓
	Aledhari *et al.* [5]	✓	✓				✓	✓	✓
	Kairouz *et al.* [21]	✓	✓	✓	✓	✓	✓	✓	✓
	AbdulRahman *et al.* [2]	✓	✓	✓	✓		✓	✓	✓
	Lim *et al.* [28]	✓	✓	✓	✓		✓	✓	✓
Healthcare	Xu *et al.* [47]	✓	✓	✓			✓	✓	✓
	Pfitzner *et al.*[37]	✓	✓	✓			✓	✓	✓
	Antunes *et al.* [6]		✓	✓				✓	✓
	Rieke *et al.* [41]		✓	✓		✓	✓	✓	✓
IoT	Zhang 2022*et al.* [55]	✓	✓				✓	✓	✓
	Boopalan *et al.* [8]	✓	✓	✓	✓	✓	✓	✓	✓
	Ramu *et al.* [39]	✓	✓	✓		✓	✓	✓	✓
	Du *et al.* [10]	✓	✓	✓	✓	✓	✓	✓	✓
Cybersecurity	Agrawal *et al.* [3]	✓	✓	✓		✓	✓	✓	✓
	Alazab *et al.* [4]			✓			✓	✓	✓
	Ghimire *et al.* [14]	✓		✓			✓	✓	✓
Blockchain	Nguyen *et al.* [36]	✓	✓	✓	✓	✓	✓	✓	✓
	Qu *et al.* [38]	✓	✓	✓	✓	✓	✓	✓	✓
	Zhu *et al.* 2022 [58]	✓	✓	✓	✓	✓	✓	✓	✓

As summarized in Table 1, most surveys extensively discuss the challenges of efficiency, heterogeneity, privacy in FL systems design, with the surveys from blockchain fileds offering the most comprehensive review. However, except for a few blockchain-based FL studies, most of the above surveys just present the same story from slightly different angles or backgrounds, i.e a server sets the model training task and delegate it to data holders to complete. This *server-domincated* cooperation framework is a narrow implementation of the FL systems. Therefore, this survey aim to fill the gap by investigating and surveying the associated tenchnologies that support more open and inclusive cooperation frameworks in FL systems, where all entities, whether they own the data or not, can benefit from it. The challenges investigated in this survey are not listed in the Table 1, to the best of our knowledge, this is the first survey that focuses on the cooperation frameworks of FL. In the following section, we will differentiate this survey from other related concepts in the field of FL.

1.2 Distinction of Our Survey

This survey focuses on exploring the innovative cooperation frameworks in FL, which will involve some FL concepts such as decentralized FL, blockchain-based FL, few-shot FL, ML related platforms and services but goes beyond them. In this section, we will distinguish our survey by highlingting the similarities and differences between these related concepts.

1.2.1 Dcentralized FL. ref: given the high scalability of modern edge computing networks, a single MEC server cannot manage to aggregate all updates offloaded from millions of devices. Therefore, there is an urgent need to develop a more decentralized FL approach without using a central server so as to solve security and scalability issues for enabling the next generation intelligent edge networks.

1.2.2 Blockchain-based FL.

1.2.3 Few-shot FL.

1.2.4 FL Systems. Federated learning, with its nature advantages in privacy-preserving decision sharing, has garnered significant attention in both industry and academia, leading to the rapid development of federated learning systems. The earliest attempt at the large-scale FL system was by Google, where FL was used to improve next-word prediction [18] and query suggesion [50] for Gboard applications. Subsequently, many novel FL systems have emerged to adapt to diverse federated training scenarios, such as Horizontal FL (e.g. TFF [1], FedLab [52], Felicitas [54]), Vertical FL or both (e.g. FATE [30], FedML [19], PaddleFL [34], FedTree [25]).

More recently, Tensorflow Federated (TFF) [1] PySyft [59] PySyTFF[1] FATE [30] FedML [19] FedLab [52] PaddleFL [34] Flower [7]

Cross-device FL framework from Huawei [54]

We aim to provide an open and shared ecosystem where every user is free to collaborate on the training of machine learning models and where privacy is protected

1.2.5 As-a-Service Business Model. In the current context of Software-as-a-Service (SaaS) [9], there are several as-a-service cloud computing frameworks that encapsulate ML tasks as services and provides unified APIs for upper layer applications. For example, Model-as-a-Service (MaaS) [12, 29, 42, 44, 60] and Machine-Learning-as-a-Service (MLaaS) [17, 20, 22, 24, 40] encapsulate model execution and model development as services. The original concept of MaaS [12, 42] was to provide re-usable and fine-grained user interfaces and visualization tools of domain-specific models (e.g wealther model, oil spill detection model) for environmental decision support systems. Subsequently, this concept has been extended to the field of recommendation systems [60] and deep learning based systems [29, 44]. However, in contrast to the focus of this survey, the aforementioned MaaS framework does not involve any user collaboration but solely provides model inference APIs to users.

As the architectures of deep neural networks (DNNs) become increasingly complex, training and maintaining DNNs become more and more challenging [16]. To address this issue, cloud service providers have introduced MLaaS, which offers an integrated development environment as a service for constructing and operationalizing ML workflows, aiming to reduce the computational resources required. MLaaS enables users to upload their data for training [20, 40, 56] or inference [17], freeing them from the responsibility of managing hardware resources and implementation. Most MLaaS providers adopt a pay-by-query business model, such as Google Vertex AI[2], Microsoft Azure Machine Learning[3] and ChatGPT[4]. However, privacy protection can be compromised when users upload data to perform inference and training in the cloud. Moverover, under this model, users are not given the ability to contribute their own models to the repository or collaborate with others to enhance the diversity of available models. While there are some ongoing efforts to offer privacy-preserving MLaaS services using techniques such as Isolated Execution Environment [17, 35] and Homomorphic Encryption [13, 20], it

[1]https://blog.openmined.org/announcing-proof-of-concept-support-for-tff-in-pysyft-0-7/
[2]https://cloud.google.com/vertex-ai
[3]https://azure.microsoft.com/products/machine-learning/
[4]https://chat.openai.com/chat

Table 2. Summary of existing deep learning model repositories.

	DS Name	Model Architecture	Modality/Task	Tag	License	Input-Output	Batch Export	# of Models
Hugging Face[5]	✓	✓	✓	✓	✓	!	✗	133,641
Model Zoo[6]	✓	✓	✓	✓	✗	✗	✗	3,426
OpenVINO[7]	!	✓	✓	✗	!	!	✓	278
Tensorflow Hub[8]	✓	✓	✓	✓	!	!	✗	1,356
Pytorch Hub[9]	!	✓	✗	✗	✗	!	✗	49
NVIDIA NGC[10]	!	✓	✓	✓	!	!	✗	527

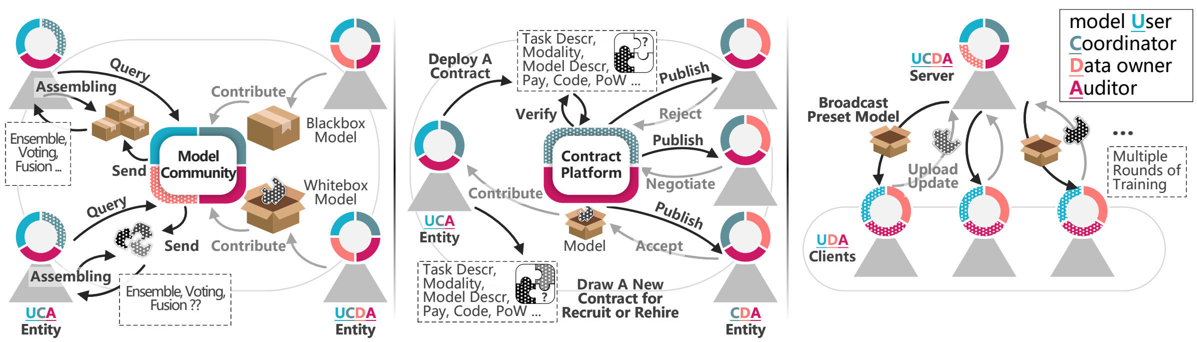
is worth noting that our focus is not solely on privacy. Rather, the FL framework we focus on emphasizes a collaborative framework where all entities involved have equal access to services and mutual benefits.

Recently, Kourtellis *et al.* [22] propose Federated Learning as a Service (FLaaS) that provides high-level and extensible APIs aim to enabling 3rd-party applications to build collaborative, decentralized, privacy-preserving ML models. However, this approach also follows the traditional server-dominated cooperation framework, which falls under the scope of previous FL surveys[21, 27, 49].

1.3 FAIR in FL

FAIR Data Principles: Findable, Accessible, Interoperable, Reusable.

Three cooperation frameworks: query-based FL, contract-based FL, writ-based FL



(a) Query-based FML (b) Contract-based FML (c) Traditional FML

Fig. 1. Cooperation frameworks of FML.

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[5]https://huggingface.co
[6]https://modelzoo.co/
[7]https://docs.openvino.ai/latest/model_zoo.html
[8]https://tfhub.dev/
[9]https://pytorch.org/hub/
[10]https://catalog.ngc.nvidia.com/models

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