Federated Learning for Medical Imaging: An Updated State of the Art

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ABSTRACT

Deep Neural networks algorithms are recently used to solve problems in medical imaging like no time ever. However, one of the main challenges for training robust and accurate machine learning algorithms, such as Convolutional neural networks (CNNs) is to find a large dataset, which is, unfortunately, not available for public usage, or it is not available when it comes to a rare disease. Federated Learning (FL) could be a solution to data lack. It can make training and validation through multicenter datasets possible, without compromising the privacy and data protection. In this paper we summarize, discuss, and present an UpToDate overview of FL for medical image analysis solutions and related approaches.

1. INTRODUCTION

Due to the recent epidemic situation of covid-19, researchers are racing to apply machine learning techniques in order to make insights from medical data (see Figure 1). AI data driven healthcare systems have known enormous success. Especially those based on medical image analysis. Several works have dealt with the analysis of medical images using deep learning-based algorithms, e.g. (covid-19 x-ray image analysis [1-4], brain tumor image analysis [5, 6], breast cancer [7, 8]). But they all agreed on the fact that the first challenge to face was the size of the dataset. That's why they have generally resorted to Data augmentation techniques [9-12].
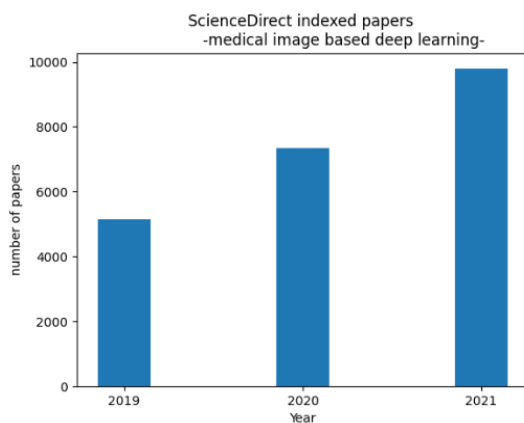

Figure 1. Evolution of the number of medical image-based deep learning papers indexed in ScienceDirect

Moreover, in classic AI machine learning, training datasets are centralized in a data lake on one machine or in a data center, and then processed. Since health data is sensitive, and legally protected, like under the General Data Protection Regulation (GDPR) in European Union countries [13, 14], it should not be accessible from outside the organization; Data privacy is in this case another challenge. Federated machine learning or Federated learning (FL) could be a solution to the privacy issue, and legal challenges related to ethics [15-21]. Beside the fact that it allows learning from non-co-located data and enables worldwide participants to contribute and benefit from globally built AI models. Federated learning concept was first presented by Google in 2016 [22, 23]. It was mainly proposed to enable mobile devices to collaborate in order to train an AI model, without having to store training datasets on data center or on one machine. Unlike "Mobile Vision API", federated learning aims to use local models that make predictions on mobile devices by bringing the model training to the devise as well [22]. Figure 2 shows an example to use TensorFlow Federated (TFF) [24], which is a Google open-source framework to experience distributed machine learning on multi participants devices.
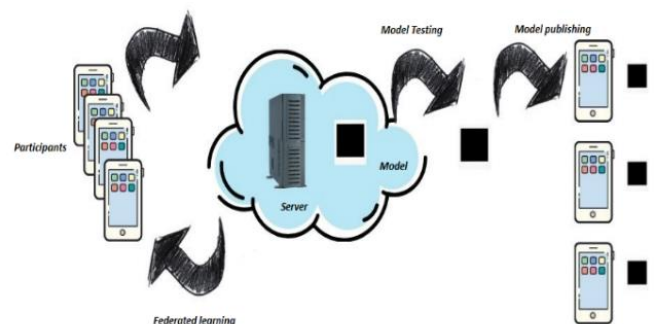

Figure 2. Example of Google TensorFlow federated principle with a coordinating server

In this case data remains on client devices. Which means data is not passed to the training server and models learn using local datasets without seeing the underlying data. This is how Federated learning could be a good solution to overcome privacy issues when it comes to learning from sensitive data. In medical image analysis, several works are recently focusing on using FL approach to create collaborative AI systems, in order to improve security [18, 19, 25, 26], and overcome accuracy challenges [27-30]. In Addition, Federated learning combined to Edge computing technologies, allows to distribute training over node devices, not only inferences. In this case, Edge devices should be equipped with important computational resources. In this paper, we first introduce a brief definition of federated learning and related paradigms. Then we provide an overview of FL based solutions for medical images analysis. Finally, we will discuss limitations and some future directions. Unlike other surveys on federated learning, our work is focusing on federated learning for medical imaging and presenting an updated state-of-the-art.

2. MACHINE LEARNING PARADIGMS FOR MEDICAL IMAGING

In medical field, Computer aided diagnosis (CAD) are computer-based systems helping doctors and radiologists to provide diagnosis with best accuracy. Medical images analysis solutions used computer vision algorithms to treat X-Rays, Magnetic resonance Imaging (MRI), Computed tomography (CT) scans Or Ultrasound. Those medical image types can be categorized as follow:
- 2D imaging: X-Rays and Ultrasound. They are taken from one angle.
- 3D imaging: Computed tomography (CT) and Magnetic resonance Imaging (MRI). Which taken from different angles.

Machine learning lifecycle is fragmented into two phases:
- Training phase: in this phase the model is optimized using large training dataset and tuning hyperparameters.
- Inference phase: in this phase, the created model is put into action to make prediction using production data.

Many works have discussed and proposed segmentation and classification solutions using deep learning algorithms treating human organs, see Table 1. Some of these works follows the traditional centralized AI paradigm. While others are respecting distributed machine learning paradigm which has been taken to the next level with federated learning approach.

2.1 Centralized machine learning

Figure 3 shows the principle of centralized Machine Learning architecture. Where all the collected datasets are centralized in a large training dataset, in this case the central server must be endowed with significant computational resources. To drive better health outcome, service providers have launched solutions for cloud centralized ML, such as Microsoft Azure healthcare. In addition to Google cloud platform, Google have recently announced the Vertex AI solution, which combines Google cloud's existing services for building ML models into one.
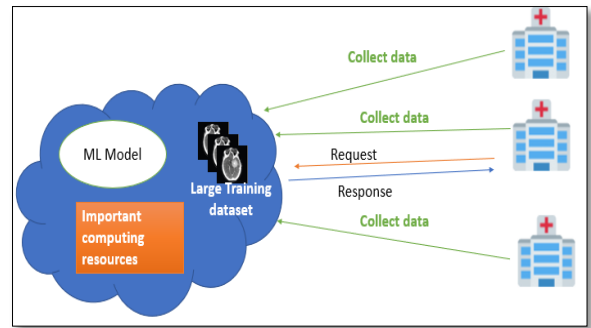

Figure 3. Centralized machine learning, where all the collected data are stored on a central server to be processed

2.2 Distributed machine learning

By storing all data on the cloud, it is most likely that users' privacy becomes compromised. Moreover, Latency could be an issue on a cloud centralized architecture; since data takes time to be stored on the central cloud server. In addition, data transfer cost is very high and not free of charges. To overcome such problems, distributed ML [31] has been tested in several works. In DL architecture, each worker (node) is building its own model using local dataset, then models' parameters are sent to a parameter server. After aggregation, the updated weights are distributed to the workers, who retains local models and send them back to the parameter server. Figure 4 explains the principle of one of the existing distributed ML architectures.

Literature organized DL into two main types: data distribution and training distribution [31, 32]. Data parallelism approach or data centric approach aims to train the same model over distributed training datasets located on different workers; each dataset is called in this case "data shard" [33]. Model information (gradients or model weights) are communicated after every step of the worker training, in case, the training is synchronous, and it is supported by *ALLReduce* architecture for example [34] or aggregated asynchronously like when a *parameter server architecture* is used [35]. Data distribution approach is generally used when the dataset overfit the memory of one device, or it can be used, as we will see in the next section, to protect data privacy, in this case the dataset will not leave the worker.

Data parallelism training approach is used when a model cannot be leaded into one computing entities memory. Its first objective is to enhance performance by splitting the model into several pieces, that will be trained over multiple workers. *BERT* model is an example of a DNN model which couldn't be trained using classic training approach [36, 37].
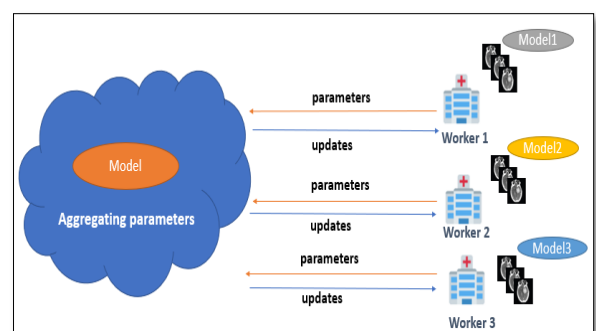

Figure 4. Example of a distributed machine learning architecture with 3 Workers (nodes)

Table 1. Applications of deep learning in medical imaging analysis paper

Paper	Research goal	Input dimension and modality	ML Paradigm	Results
[38]	FedDis: Disentangled Federated Learning for Unsupervised Brain Pathology Segmentation	2D, MRI		FedDis disentangles the model parameters into shape and appearance, and only share the shape parameters mitigating the data heterogeneity among the clients. The global FL model is then employed to segment anomalies on unseen sites
[39]	skin lesion and spinal cord segmentation and classification	2D, MRI	Server – Client Federated Learning	The proposed method can significantly outperform FedAvg and FedProx based on most of metrics, including DSC, CC, JI, and ASD.
[40]	early breast cancer development	2D, X-ray	Centralized Model	The proposed method was instantiated with two datasets, one clinical dataset and one publicly available dataset, and classification accuracies of 88.7 and 70.0 percent were obtained
[41]	COVID-19 lesion segmentation in chest CT and pancreas segmentation in abdominal CT	3D, CT	Distributed/Federated Learning	CIFAR-10 classification with heterogeneous partition. "Auto-FedAvg-N-Dirichlet" achieved the best final accuracy of 88.98%
[42]	Covid-19 Lung	3D, CT image	Federated transfer learning	the CNN-based AI model trained using a privacy protecting federated learning approach is effective in detecting CT abnormalities in COVID-19 patients. The wide generalizability to regional and international external cohorts, benefited from including diverse datasets, shows the promise of AI providing low-cost and scalable tools for lesion burden estimation to support clinical disease management. Code available: https://github.com/med-air/FL-COVID
[43]	Multi-site fMRI analysis using privacy-preserving federated learning and domain adaptation: ABIDE results	3D, Functional MRI	Federated learning Client server	Accuracy 76%
[15]	an image segmentation method to identify brain tumor	3D, MRI	Server-Client Federated Learning	The FL systems are compared with the data-centralized training. The proposed FL procedure can achieve a comparable segmentation performance without sharing clients' data. In terms of training time, the data-centralized model converged at about 300 training epochs, FL training at about 600
[44]	Brain segmentation Braintorrent	3D, MRI	Federated Peer to Peer	the models in BrainTorrent converges faster and reaches an accuracy similar to a model trained with pooling the data from all the clients. Accuracy 86%
[45]	predict two-year lung-cancer survival		Distributed Learning/federated learning;	A comparison of the performance of this distributed solution, evaluated in six different scenarios, and the centralized approach, showed no statistically significant difference (AUCs between central and distributed models), all DeLong tests yielded p-val > 0.05.

Other DL types are discussed in the ref. [46], such as Graph parallelism, Task parallelism and Hybrid parallelism.

Federated Learning is considered as a subset of Distributed Learning by researchers [47, 48], and even the next level for the DL approach. Federated learning (FL) aims to build a ML model using data located on multiple sites [46]. In a Medical context, deep learning models for medical images analysis, could be trained at each participating institution using local data, without the need to share patients' sensitive information. Recent works have demonstrated that FL model performance metrics like accuracy, recall and F1-score, are equal or sometimes even better than a single institution trained model [29, 39, 40, 49, 50].

Federated learning applied to medical image analysis systems, allows participating organizations:

- *During training phase*: the first limitation for this type of systems, is the lack of data. Due to the rareness of disease. FL enables participants to collaboratively elaborate a better ML model than what it can be create alone.

- *During inference phase*: it allows to organizations to make predictions and diagnostics for a new patient without sharing personal information. While benefiting from the experiences and knowledge on the institutions participating in federated system.

Since no data transfer is needed in FL, data privacy is insured. However, in medical images, researchers are trying to standardize privacy prevention techniques. Such as Anonymization, pseudonymization and re-identification, see an overview on those techniques [45, 51]. The most used privacy prevention techniques used for medical images still the Anonymization [39], which consists in removing all patient data from the image, patient name, gender, etc.

3. FEDERATED LEARNING ARCHITECTURE

Federated learning was first introduced in combination with an Edge computing technique [22, 23, 48], Google introduced FL Architecture to improve language models on mobile phones. One of the numerous benefits of this approach is that it allows to obtain smarter models, that are trained indirectly on data from multiple users. So, there is no need to create a central database to store all the datasets. FL allows for smarter models, lower latency and less power consumption, so there is no need to centralize the training on one robust machine or in the cloud.

Like in Distributed Learning, federated learning can involve a parameter server (also called coordinator) which is a central aggregation server, used to first send an initial model to the participants (also known as clients), and aggregate after that all the model updates received from the clients. But it is not the only possibility to design a federated learning structure, FL system could be designed in peer to peer, in this case there is no need to use a coordinator server.

Participating Edges or data owners may or may not be mobile devices. In medical context for example, edges could be medical organizations exchanging knowledge to create a smarter medical imaging model.

3.1 Client server

In a client server Federated learning architecture, all the Edge participants are connected to a parameter server. They are first initialized with a primer model, then every data owner trains his model using local data, without sharing it. Updates are after that sent back to the coordinator server, and communications are encrypted using homomorphic encryption [52, 53]. Updates (model weights) are aggregated using Federated average (FedAvg) [54]. this operation is repeated until the model converges, or until a fixed number of rounds is reached. Figure 5 shows an example of FL client server-based architecture with 3 clients.
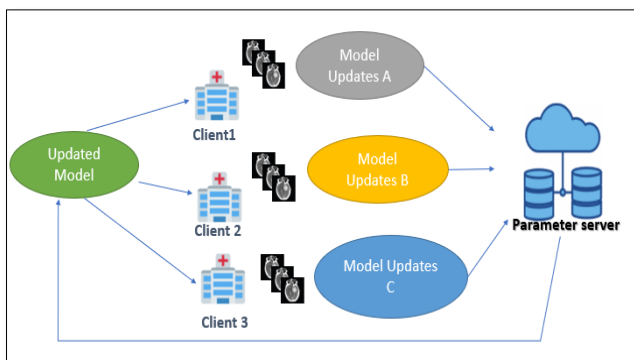

Figure 5. Example of client server-based FL architecture

3.2 Peer to peer

Both Server client architecture and Peer to Peer architecture are Horizontal Federated Learning. Horizontal federated learning is generally used when data owners have datasets with same features but not the same samples. It is similar to horizontal partitioning of a database table; every set of rows is characterized by the same columns (features).

Peer to Peer Federated learning doesn't need coordinator server. The N Participants are called in this case Trainers or distributed trainers or workers. All the trainers are working on the same model and communicating weights between then. Since there is no coordinator, workers could send model weights according to cyclic transfer approach, Or random transfer. In the first approach, the worker on the top of the chain is designated for sending its model parameter to the next worker and so on. This operation is repeated until the model converges or until a k number of rounds is reached. Random transfer, the target trainer selects a random worker, to whom he will send his model weights and so on. In Medical imaging, *Braintorrent,* a server-less peer-to-peer federated learning environment *for brain segmentation using decentralized fully convolutional neural network (FCNN)* [44]. The proposed solution reaches performance similar to a traditionally trained model, in centralized learning environment [55].

4. FEDERATED TRANSFER LEARNING

In some cases, the discussed federated learning architectures are not suitable, e.g. if the trainers datasets are not sharing enough features, or if the amount of labeled data is limited. In this case, federated learning could be combined with transfer learning, to overcome these challenges. Transfer learning is a technique used to reuse and adapt ML models from similar domain or tasks. In medical imaging field, federated transfer learning was used in the ref. [42] to detect Covid-19 abnormalities in Lung medical images using a CNN based model.

Other works are focusing on using transfer learning in order to overcome the availability of medical image semantic annotations [56]. TL make it possible to train CNNs by sharing and fine tune similar parameters. However, the authors [57] studied the effectiveness of TL in medical imaging field, and confirms that it still offers good opportunities of exploitation.

5. BLOCKCHAIN AND FEDERATED MACHINE LEARNING

Medical application using blockchain technology are getting more and more attention, since it could be a good solution to improve privacy preserving and data security. Federated learning impower privacy preserving by not sharing local dataset between trainers. However, researchers have shown that somehow it is possible to inject malicious dataset into the federated structure [48, 45] which will have an impact on the accuracy of the generated Model. Blockchain is a technique that can be thought as a distributed database, which make tracing usage of data possible. We can know who used a dataset by the past, and the most important thing is to know the origin of dataset. In medical field, blockchain include the documentation of the diagnosis and their author, it also enhances the possibility to access information in medical report. It is giving more control on who has manipulated patients' health data [58].

Blockchain is an immutable, encrypted, distributed ledger technology where data can only be appended (see Figure 6). Blockchain implementation for medical images is discussed in [59, 60]. In federated environment, where edges are hospitals, and with public blockchain, it could be possible to append transactions to the blockchain given permission to other trainers to view a patient's medical images. In 2018, two doctors at University of Illinois at Chicago, presented a project

under the title "Diagnosis Protocol Using Blockchain to Accelerate Artificial Intelligence in Medical Imaging". This project is using Blockchain technology to share medical-images and make it possible to researchers and practitioners (pathologists and radiologists) to enhance their diagnosis potential. The project aims to share medical images, compare data and correct errors, in order to provide enough training data for AI medical image-based diagnosis systems.
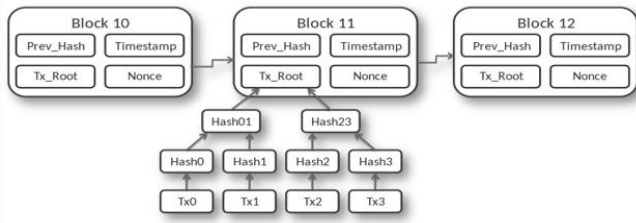

Figure 6. Blockchain structure of Bitcoin, source: https://commons.wikimedia.org/w/index

6. FEDERATED LEARNING DEVELOPMENT FRAMEWORKS

Cloud Service providers like Google, Microsoft, Amazon and IBM have proposed cloud-based solutions supporting distributed learning. MapReduce is the main component to insure distributed computation. McMahan et al. introduced in 2016 Federated learning approach for training Neural networks models on the edges (mobile phones, and in medical fields it could be medical institutions), while preserving data privacy. FL systems are mainly using three components (e.g., server client FL):

- Server (parameter server aggregating model weights).
- Computation framework and communication.
- Parties (workers or participating clients).

Federated learning architecture for medical image-based solutions where parties are Institutions, is different from FL solutions using mobile devices as edges. In fact, there is two types of FL based on type of parties [61]:

- Cross-silo: where parties are organizations or data centers. With a limited number and rarely changing. Data distribution in this case is usually non identified Id.
- Cross-device: where parties are mobile devices and IoT devices, their number is more important than cross-silo system, and they could join or quit the parties list at any time.

Table 2 shows the most important FM frameworks used in medical imaging:

Table 2. The most important FL frameworks used in medical imaging

FL Framework	Provider	References
Tensorflow Federated (TFF)	Google Inc	[22-24, 62]
Pysyft	The open community Open Minded	[25, 63]
Nvidia Clara train	Nvidia corporation	[64]

7. DISCUSSION AND OUTLOOKS

At present, medical imaging-based AI systems have a great success. AI based diagnosis systems can detect minor lesions, making discovery of advanced diseases more relevant. However, most of the actual studies estimate diagnostic accuracy by calculating sensitivity and specificity [65, 66]. The authors [67] are discussing the fact that AI models are focusing on lesion detection of minor abnormalities in medical images and not using a patient-centric approach. This can lead to enhance sensitivity and increase false-positive diagnosis. Although, Computer vision based medical solutions, can extract image pattern that are not easily identified by practicians in traditional reading.

Besides the cost of training a computer vision AI model on centralized machine is not free of charges. Centralized AI is generally migrated to the cloud, which induces a new problem concerning the cost of communication with the server, in the training phase as in the inference phase as well as the quality of the internet communication.

Since 2016, when google announced her federated learning approach to train deep learning networks [23]. This approach helped researchers in medical field to re-evaluate the existing AI medical image-based solutions. In order to overcome the lack of data; by involving multiple institutions. And to overcome data privacy challenges, since data will not leave organizations. Moreover, medical institutions will collaboratively learn a shared model, while reducing computational costs.

Federated learning combined to other revolutionary techniques such as Blockchain could make AI model benefits of more efficient privacy preserving tools [68-70]. Solutions in Teleradiology [71] are attracting more and more researcher's attention. Combined to Blockchain technology, it allows to practitioners (physicians and radiologists) from different hospitals to distribute medical interpretations and using medical images like in a marketplace. While tracking image manipulation history and the original source of the image.

Federated learning as discussed in this paper is the next generation of AI medical solutions. it opens new avenues of research in the medical and AI fields, by reviewing the precision of existing models or by proposing new architecture that reinforces and optimizes the security of health data.

8. CONCLUSIONS

Recently, federated Learning in medical imaging have known an enormous success. FL solution as discussed in this survey, enables to overcome centralized learning challenges such as data lack, data leakage and privacy preserving. Combined to other technologies like Blockchain and Edge computing, it could offer a good package for deep learning model training process. Besides Horizontal federated learning: Client-Server or even in peer-to-peer architecture, Federated transfer learning is used to benefit from existing similar models when it is difficult to create its own model from scratch, due to the shortage of dataset for example. This paper is simplified up to date overview of federated learning for medical imaging technics, destinated to researchers, medical practitioners and whoever wants to discover how federated learning is revolutionizing AI based medical solutions.

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