Federated Learning in Medical Imaging: Part I: Toward Multicentral Health Care Ecosystems

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Abstract

With recent developments in medical imaging facilities, extensive medical imaging data are produced every day. This increasing amount of data provides an opportunity for researchers to develop data-driven methods and deliver better health care. However, data-driven models require a large amount of data to be adequately trained. Furthermore, there is always a limited amount of data available in each data center. Hence, deep learning models trained on local data centers might not reach their total performance capacity. One solution could be to accumulate all data from different centers into one center. However, data privacy regulations do not allow medical institutions to easily combine their data, and this becomes increasingly difficult when institutions from multiple countries are involved. Another solution is to use privacy-preserving algorithms, which can make use of all the data available in multiple centers while keeping the sensitive data private. Federated learning (FL) is such a mechanism that enables deploying large-scale machine learning models trained on different data centers without sharing sensitive data. In FL, instead of transferring data, a general model is trained on local data sets and transferred between data centers. FL has been identified as a promising field of research, with extensive possible uses in medical research and practice. This article introduces FL, with a comprehensive look into its concepts and recent research trends in medical imaging.

Key Words: Federated learning, privacy-preserving machine learning, medical imaging

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INTRODUCTION

Deep learning has shown great promise in the field of radiology. It has been used extensively in various medical imaging domains and has already helped clinicians and radiologists in numerous ways. The field of radiology has dramatically benefited from deep learning research. It has been shown that deep learning can improve the existing models of tumor detection, from early processing stages such as image enhancement in MRI and CT, noise reduction, lesion detection and segmentation, and disease monitoring. All these areas have shown great promise for the use of artificial intelligence (AI) in clinical settings.

Deep neural networks are made up of many layers with billions of parameters, and they train to learn a complex, high-dimensional mapping from raw input data to desired labels [1]. The main issue with training deep neural networks in real-world medical practice is that a massive amount of diverse data is needed. A neural network trained on a single data set from a single institute may be easily overfitted, resulting in a strong bias toward that institute and poor generalization. Furthermore, latent patterns in one client's imaging data may influence the performance of a neural network in ways that have nothing to do with the actual biologic way in the image. For example, data sets containing only one modality or images registered on a specific atlas may bias deep learning models toward that modality or atlas, capturing irrelevant data as significant predictors. The quality of data of a single institution

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depends on a variety of factors such as the number of patients, type or number of imaging machines available, and the number of experts available at that institution. Not all health care facilities have vast amounts of diverse imaging data, and deep learning models are thus usually trained on limited data sets. This makes clinical decision making burdensome given the low number of cases, which happens more often in rare diseases.

One potential solution to this data shortage is to obtain imaging data sets from different clients. This method has the potential to increase both the amount and diversity of data collected. The most frequent method for establishing such a collaboration is to centralize vast and diverse data sets from multiple institutions and train a deep neural network on an accumulated data set situated in a central hub, as can be seen in Figure 1. However, this technique is fraught with difficulties; strict national or regional privacy rules, such as General Data Protection Regulation in Europe or HIPAA in the United States, preclude institutions from easily sharing their patients' data. Other impediments may arise from the multiple stakeholders, including hospitals, patients, researchers, medical physicians, and industrial corporations, each pursuing their interests. The significant amount of time and effort (and hence money) that an institution spends to collect and clean data makes it hesitant to share it with other institutions.

Recent advancements in privacy-preserving AI algorithms play an essential role in solving this. They enable researchers and institutions to train their networks on diverse imaging data from multiple institutions while ensuring that data will be kept locally, thus avoiding many issues concerned with building and maintaining an extensive central database. A general methodology in deep learning is decentralized or distributed learning. Distributed learning can be defined as a group of algorithms in which multiple clients do part of the computation or data storage tasks. The data distribution allows numerous clients to participate in the learning process and enables higher performance with a larger input data size. It generally involves multiple nodes and clients doing partial computation, each on their own local database. Distributed learning is done for a variety of reasons, including performance boost and large-scale computation. Federated learning (FL) is a version of distributed learning tailored for tasks in which data privacy is essential so that researchers can preserve privacy while performing distributed learning. This feature enables health care centers to train deep learning models without compromising the privacy of their local data.

FL ALGORITHMS

A deep learning model is a form of algorithm based on artificial neural networks. It uses high volumes of data to extract patterns from them. Artificial neural networks generally consist of millions of parameters called model weights. Training a model is the process of tuning the parameters of the neural network to perform a task (eg, detection, classification, or segmentation in the imaging domain). The training process is done by exposing the model to a specific data set for several rounds. More rounds and more extensive training data generally lead to more accurate parameter tuning and better model performance.

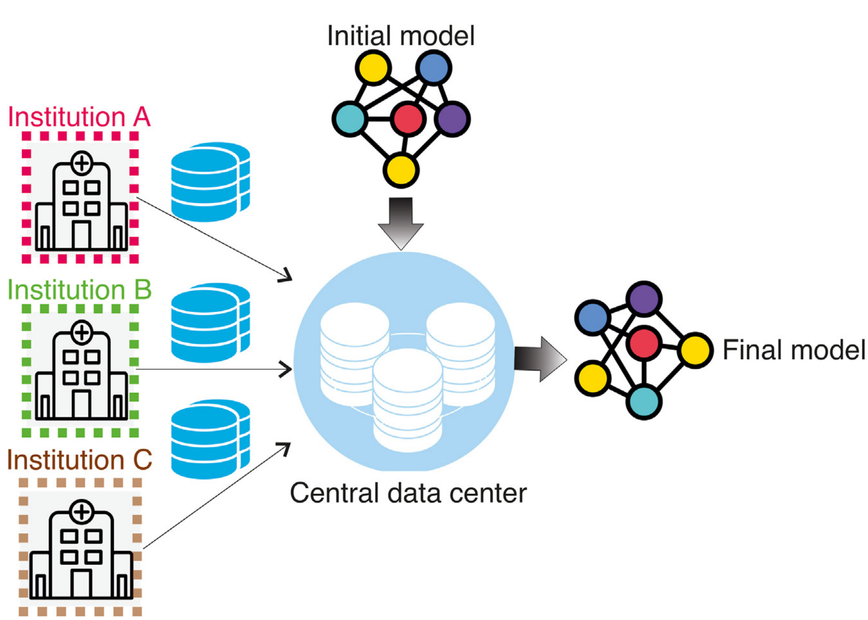

Fig. 1. Centralized data sharing.

Generally, models' size depends on their complexity and the number of parameters they have, regardless of how much data they were trained on. Popular deep learning models have a size of no more than approximately 150 MB [2].

As a result, complex patterns of enormous imaging data sets can be encoded in models with much smaller sizes. One immediate advantage coming from this feature is in distributed settings. Sharing models in these situations would be much more practical than sharing data. Sharing models are thus subject of interest in distributed settings involving voluminous data (eg, high-resolution images or multislice MRI and CT scans).

FL is a distributed learning method in which multiple participants train (or update) a local model on their data without actually sending data to the central node. A global model is updated according to the updated models received from participants. This way of training allows researchers to ensure the privacy of models and distributes the heavy computing process. FL is also efficient in communication, because generally only model weights will be communicated in this setting. In this regard, it tackles the infrastructural barriers of moving large volumes of data from one institution to another. Various ways to harmonize global and local model updates result in multiple versions of FL. Generally, federated networks require multiple clients who hold the data and perform the local training and a central trusted server, which manages the whole process.

Each client trains a model it gets from the central server on its local data. To get the model, the client sends a request to the cloud server, informing the server that the client is ready to start the local training session. Then the request is processed, and the latest global model is sent back to the client. Next, the training session starts using the received model and local data. After the local training session is finished, the model is returned and the center accumulates the received updates. Finally, the global model is updated by the server based on the received model and notifies the client that one training round is successfully completed. A schema of these steps can be found in Figure 2. It is important to note that the model used for training in the hospital has to be the same type as the model being used by the central server. For example, both have to use the format in the same programming language. So practically, any form of transfer that preserves the type and information of the local model can be used. There is no certain requirement for communication technology. The information can be delivered using any form of file transmission (eg, file transfer protocol, secure shell protocol file transfer protocol, hypertext transfer protocol, and hypertext transfer protocol secure) or third-party software using those protocols. There are several Python-based packages designed for transferring models in federated settings.[3]. Open source Python packages like Jupyter notebook are preferred to run FL applications. However, some models support other platforms such as web, mobile and Broadcoms' Raspberry-pi.[4]

For a hospital to join an FL network, a collaboration between different experts from various areas might be needed. An institutional review board or ethical committee determines how a hospital participates in a federated network and the level of trust to other involved parties. This committee usually suggests the steps to prepare data so that the hospital can connect to other hospitals. PACS managers and hospital technologists access, prepare, standardized, and deidentify data according to the guidelines prepared by the review board. Data standardization generally follow the FAIR principles. The FAIR principle consists of Findable, Accessible, Interoperable, and Reusable data collection [5]. FL algorithms that could not use the data from various sites because of the difference in the data type could easily read and analyze data collected in the FAIR manner, which helps add more clients to the network. One example is language protocol differences in sites. Uniform Resource Identifier could represent the clinical data, enabling automated algorithms to read clinical text queries standardized with FAIR principles [6]. Integrating FAIR data collection and adding it as an initial step of building an FL network could strengthen the FL networks and entice more institutions to join the networks. The FAIRified data will be then given to data scientists and

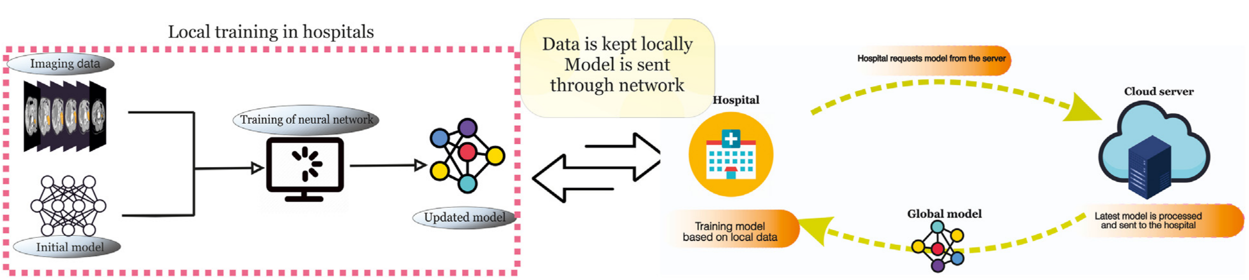

Fig. 2. Communication between client and server, exchanging the model.

machine learning engineers to build an FL framework. Clinicians participate by providing annotated data and expert support. They can also take part in assessing models and provide expert feedback.

APPLICATIONS IN RADIOLOGY

Although FL still needs to be improved before it can be used on a large scale, it has shown promise in a practical medical imaging context in a few implementations in medical images, leading to improvements in patient care. FL can assist underrepresented patients in small clinics in which they are a minority and may be overlooked and bring them into a pool with many other similar patients. FL has shown great promise in the research for patients with coronavirus disease 2019 (COVID-19); it was investigated and reported that FL had a clear impact on patient care in a large-scale study on patients with COVID-19 across 20 centers on five continents [7]. The centers used chest x-ray imaging data in addition to clinical data to determine hospital triage for level of care and oxygen requirement in patients with COVID-19. They demonstrated that the FL model works best for clients with limited data sets. The model performance for these clients is significantly improved compared with when they were trained on their local data, resulting in a change in the patient situation.

Another discovery was that medical centers with unbalanced data had some classes with few samples, resulting in underrepresented categories. These clients saw a significant improvement in prediction for those patient categories, which is especially important because, in COVID-19, patients with severe symptoms are generally in categories with fewer samples than a larger pool of patients with moderate symptoms. However, their care is more critical and requires more attention. In the field of applied FL in radiology, there are numerous projects. As an additional effort to the Brain Tumor Segmentation (BraTS) challenge, Intel and the University of Pennsylvania launched an extensive effort. This challenge was based on a data set provided by the University of Pennsylvania's Biomedical Image Analysis section [8].

The BraTS data set from the 2018 BraTS challenge was made available to the public. The data set consisted of MRI images of the brains of patients with glioma, gathered from several studies in different institutions. Four radiologists manually annotated the MRI images, categorizing them into various tumor classes. Tumors were classified into four types. U-Net was the deep learning model used to segment tumors, and the FL network was made up of one master node and numerous clients, each with their data. Two hypothetical clients were developed, and the data set was assigned to them to evaluate the FL model. To examine different data distribution algorithms, they first divided the data randomly into silos. They also assigned data based on where it was obtained, resulting in nonhomogeneous data. After finishing the local training, many clients delivered a model. The central server received updated models from all parties, selected the best models, and returned the aggregated models to the clients. This training strategy allows both the server and the clients to enhance their performance. After receiving the updated model from the central node, clients work on a better model each round. As a result of their experiments, they concluded that in the task of semantic segmentation, federated training could produce MRI segmentation masks that were better or comparable to models trained on premise.

Sheller et al [9] proposed a project on brain tumor segmentation using FL and achieved comparable accuracy to centralized data sharing. They demonstrated that increasing the number of collaborators improved the FL algorithm's performance and generalizability. Another study suggested a patient similarity analysis to find comparable patterns within different hospitals for possible similar treatments [10]. The goal of this study was the identification of patients with similar profile while protecting their privacy and personal information. They created hash codes to represent patients and a federated environment to control the entire process to achieve this goal. The hashed data had the advantage of being resistant to reverse engineering or adversarial model attacks. They could anticipate five diseases independently, using balanced and unbalanced data to evaluate their proposed algorithm.

Another effort was made to explore the structural relationship of the brain without revealing any data. The authors used principal component analysis to uncover anatomical relationships between diverse data sets in a federated setup [11]. Federated principal component analysis could extract features from MRI pictures from several medical institutes. Their technique was validated using several databases, including The Alzheimer's Disease Neuroimaging Initiative Parkinson's Progression Markers Initiative, The Minimal Interval Resonance Imaging in Alzheimer's Disease, and UK Biobank [12].

Balachandar et al [13] used FL to address the issue of data variability across institutions. They used chest x-ray data set to classify chest scans. Also, they classified retinotherapy data with their proposed method.

FUTURE OF FL RESEARCH

Several research trends show that FL research is growing. The future direction of FL is to integrate it with big data technologies. After establishing FL networks, data could be added to the existing networks in real time. Allowing the training and inference phase to work in real time is a potential future direction of FL networks. This can be streamlining preprocessing, training, and data handling.

It is expected that FL networks include medical imaging data and work on all other types of medical data. Most of the recent FL implementations make use of imaging data with neural networks specifically designed for image processing. However, other formats of data, especially electronic health records (EHRs), are starting to be added to the current networks and are a contemporary development topic. EHR data include a wide variety of information from treatment histories to past medication in addition to the medical imaging data; EHR data can generally be in text, medical letters, categorical data, quantitative numbers, and binary data [14]. Incorporating this information into the imaging data could help develop better models. For example, making various treatment plans as an input variable to a deep learning model could help radiologists choose between treatment plans. Using EHR data could also help determine the type or stage of disease, as researchers recently used EHR to detect Alzheimer's disease [15].

There is still research to convert EHR data formats to a format usable by deep neural networks. Some progress has already been made using natural language processing to make text records available for deep learning [16]. For this purpose, researchers developed a data standardization framework to extract meaningful features from text data and make them available in the machine learning pipelines. Medical images combined with genomics data could also be a line of research. Because genomics data are not as prevalent and readily available as imaging data, the data limit problem in genomics is a much bigger issue than medical imaging. Hence, FL can play a pivotal role in bringing genomics data to the medical imaging field. Medical centers can communicate through FL with all types of their data in the future, so the collaboration level is expected to expand.

CONCLUSION

FL is a developing and growing technology that has influenced a variety of aspects across several fields. The main reason that hospitals are moving toward FL technologies is that privacy and security are their main priorities, and there are strict rules regarding the privacy of patients' data. FL offers straightforward and secure data access for institutions and uses the capacity of several institutions to enhance radiology research while overcoming the limitations of privacy and data-sharing laws and regulations. Building a federated environment helps in achieving performance equivalent to a centralized setting. It can foster global cooperation among several institutions, therefore redefining the paradigms of AI in radiology. This article should be helpful for radiologists and data scientists who want to learn about FL ideas and their applications in radiology.

TAKE-HOME POINTS

- With FL, setting up multicentral medical image processing networks is smoother than always. In the past years, data privacy in multi-institutional networks has been a serious concern. This problem can be successfully addressed by sharing models instead of data. FL explores the ways to keep sensitive data in private silos and train a deep learning algorithm by only using models.
- The infrastructural requirements for federated networks include data storage technologies, standardization pipelines, data deidentifiers, and strong processing units. Having reliable network access is also vital to establishing large-scale links. Hence, a collaboration among PACS managers, clinicians, data scientists, and clinical technologists might be required to set up this whole pipeline.
- Several radiology tasks were performed on CT scans and MRI images with FL. The algorithms had promising results for COVID-19 detection, brain tumor segmentation, and retinotherapy.
- One future development of FL could be its integration with big data technologies. Also, another line of research is to make the algorithms more versatile so that EHR data could also be used. Natural language processing is an active line of research to enable the combination of textual and imaging data. This combination has been shown to improve the diagnosis in patients with Alzheimer's disease.

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