Review

Federated Learning for Analysis of Medical Images: A Survey

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Abstract: Machine learning models trained in medical imaging can help in the early detection, diagnosis, and prognosis of the disease. However, it confronts two major obstacles: deep learning models require access to a substantial amount of imaging data, which is a hard constraint, and the patient data is private and sensitive, so it cannot be shared like 1 other imaging data in computer vision. Federated Learning (FL) offers an alternative by deploying many training models in a decentralized way. In recent years, various techniques that leverage FL for disease diagnosis have been introduced. Existing survey articles have analyzed and collated research about the use of FL in general. However, the particular component of medical imaging is ignored. The motivation behind this survey paper is to fill up the research gap by providing a comprehensive survey of FL techniques for medical imaging and various ways in which FL is employed to provide secure, accessible, and collaborative deep learning models for the medical imaging research community.

Keywords: Federated Learning, Medical Imaging, Classification, Segmentation, Detection, FL Frameworks

Introduction

Over the last decade, Machine Learning (ML) has shown remarkable success in early disease detection, diagnosis, and prognosis (Khan and Robles-Kelly, 2020). However, it faces two challenges, (Khan and Robles-Kelly, 2020) deep learning models require access to a considerable amount of imaging data, which is a hard constraint (Gupta *et al*., 2023), medical imaging about the patient is private, and of a sensitive nature and, therefore, cannot be shared like other imaging data (Liu *et al*., 2023). In response to these challenges, a secure and collaborative ML framework has emerged, called Federated Learning (FL) (Li *et al*., 2019), which can assist with training an algorithm faster while using less training data. FL, which protects patient privacy and enables collaborative model training across institutions, transforms medical image analysis. It uses edge computing for effective processing, enabling cross-institutional research and knowledge sharing without centralizing sensitive data. Moreover, it facilitates domain adaptation and transfer learning, guaranteeing that models generalize well across a variety of datasets while upholding data sovereignty and legal requirements. FL works on specific tasks faster and more efficiently (Deiana *et al*., 2020) than humans ever could. This survey explores the effectiveness and applications of FL in introducing privacy to ML solutions based on medical imaging.

Deep learning methods require a large amount of data with variations to perform efficiently (Sarker *et al*., 2021). However, it is quite challenging to collect the data from various sources and put it in a central place due to privacy concerns (Ratta *et al*., 2021). Even if the data is secured from external threats, the data leakage from the internal person is quite high, which makes the data owner reluctant to share the data. FL is the recent approach introduced by Google in 2016 (McMahan *et al*., 2017), that enables the training of the universal model without gathering the data in one place (Nasri *et al*., 2023). It trains the centralized model using decentralized data (Ye *et al*., 2022). The data stays in its place of origin and the model is trained on the device or location where the data is produced (Zhu *et al*., 2023), which reduces the hardware cost needed to store the data (Jimenez Gutierrez *et al*., 2024). In contrast, FL divides the data into small chunks, which speeds up the analysis process (Reisizadeh *et al*., 2020). As a result, these smaller datasets can be analyzed in less time and with less computing power (Bousbiat *et al*., 2023).

This survey enlightens on FL usage in medical imaging and has a strong focus on FL frameworks for cancer analysis. Furthermore, concepts and types of FL are also discussed in this study. The section breakdown of this study is given below; it will have an introduction followed by an overview of FL with different types of FL, FL framework for cancer analysis, and the use of FL in medical imaging. At last, the conclusion will be presented.

Federated Learning Overview

The concept of FL was first announced by Google in the year 2016 (McMahan *et al*., 2017). FL is a method which slices the data into smaller portions and conducts analysis on each unit of the dataset independently (Posner *et al*., 2021). After the study is completed, the model is built by using all of those smaller datasets (Połap and Woźniak, 2022). FL aims at solving two main problems of the existing DL approaches in the first case. Firstly, it is an expensive affair to implement deep learning models in a discrete architecture as the data has to be transferred across the faculties (Zhang *et al*., 2018). For this reason, FL can be applied for distributed fashion and with fewer datasets (Kang and Ahn, 2021). Second, obtaining deep learning models are used to perform a single task, for parenthesis voice recognition (Khurana *et al*., 2021) or image recognition (Li, 2022). However, most of the times such companies needs to redeploy the whole model any time when they wish to take advantage of such models for other purposes such as generating new text or images in construction (Langlotz *et al*., 2019; Połap *et al*., 2021). FL is intended to reduce the ‘performing Enterprise Change’ (Wang *et al*., 2022a) and ‘Time to Recover’ (Jiang *et al*., 2023) by decentralized and, accordingly, income flows across the goodness of patience.

Malik *et al*. (2023) DMFL Net model gathers data from different types of hospitals then constructs the model using DenseNet-169.

The unique characteristics and challenges of federated learning in medical imaging are discussed in Singh *et al*. (2023). Federated source FREE Domain Adaptation (FFREEDA), in Shenaj *et al*. (2023), is described where the server only accesses a source labeled dataset for pretraining and the clients' data is unlabeled. LADD takes advantage of the pre-trained model's expertise by using self-supervision and ad-hoc regularisation approaches for local training and introducing a novel federated clustered aggregation scheme based on the client's preferences. FedDebug (Gill *et al*., 2023) a framework for systematic fault localization, makes two unique advancements in FL debugging. First, FedDebug uses record and replay techniques to build a simulation that accurately represents live FL, enabling interactive debugging of real-time collaborative training in FL. A realistic approach based on iterative model averaging for the federated learning of deep networks and a thorough empirical evaluation taking into account five distinct model architectures and four datasets is presented in citemcmahan 2017 communication. Kairouz *et al*. (2021) summarised the most recent developments and listed a significant number of open problems and challenges related to FL. FL model is given below in Fig. (1).

To create a federated model, a model owner (server) first trains the model it created (Lian *et al*., 2022). The model owner then extracts the model and distributes model building blocks to other organizations, including data, hyperparameters, and an architectural description (Yoo *et al*., 2022). The model is then built and executed locally by these other organizations using the model building components (Banabilah *et al*., 2022). The server and other organizations can utilize the model to generate predictions once it has finished training (Li *et al*., 2023). The initial model is then updated by the server by combining the parameters from the clients' models (Lu *et al*., 2022).

Although FL is a relatively new technique, it has already been implemented in projects such as OpenFiscar, an open-source tool (Elayan *et al*., 2021) for generating fiscal forecasts, and OpenML, an open-source tool for model exchange and collaborative model building (Guberović *et al*., 2022). Darzidehkalani *et al*. (2022), FL enables the participants to train a local model on their data without sending the actual data to the server. A global model is updated by the participants. This ensures the privacy of data. FL tackles the infrastructural barriers of moving large volumes of data from one institution to another. It requires multiple clients who hold the data and perform the local training. A central trusted server manages the whole process from the initial model to the final model.

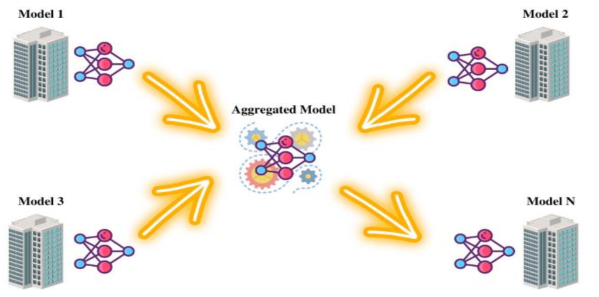

Fig. 1: Use of FL across the organizations. All the models trained by different organizations are aggregated by the server to get the final result (Mammen, 2021)

The equation of federated stochastic gradient descent and the updating of weights is presented below:

$$s := s - \frac{\eta}{x} \sum_{l=1}^{x} \nabla Q_1(s) \quad (1)$$

Types of FL

FL is a concept based on leveraging supervised ML algorithms to optimize training on a distributed network (Huang *et al*., 2022). There is more than one way to approach this concept (Mohamad *et al*., 2022), we will start by having a look at the various types of FL. It can be categorized into three different types-model-centric FL (Mohamed and El-Gayar, 2022), cross-device FL (Yang *et al*., 2022), and horizontal FL (Guo *et al*., 2022). Some FL types are discussed.

Model-centric FL (Mohamedand El-Gayar, 2022): In this model employees generate a model of the skill set of which they are based a model inputted into the system through cross device data. on examples fed into the system via employees' cross-device data. The purpose of this model is to optimize training for all of them.

Cross-device FL (Yang *et al*., 2022): In this federated learning (FL) system, the examples for the employees are formed from the data obtained from their devices. Thereafter, this data is used in training models aimed at optimizing the training of each individual employee.

Horizontal FL (Guo *et al*., 2022): In this type of FL, employees are trained on one skill that cuts across different domains in the organization.

Roy *et al*. (2019) propose BrainTorrent which is central free FL framework targeting medical applications.

Silo FL (Zhang *et al*., 2023): In this type of FL, one group passes their skill set and knowledge to employees from other departments. For instance, an engineering firm can guide an HR group on the application of their software.

Vertical FL (Feng, 2022): In this type of FL, employees in a particular skill set are taught more advanced skills that are still within the same discipline. For instance, a marketing department can be advanced to the utilization of marketing department.

Data-centric FL (Huang *et al*., 2023): In this type of FL, central modelling is nonexistent. The AI algorithm is what acts as the central theme in this case the label to the users' models created for training the algorithm is the training algorithm. There is no need sharing the data across devices of employees.

Federated transfer learning (Zhang and Li, 2022): In this type of FL, a particular AI model utilized in the organization teaches skills from one employee to other employees from other departments. This can address a situation whereby people return to the organization after being out due to looking after sick people.

Limitations and Challenges of FL

The continuous increase in the amount of available data and computation has given new dimensions to the design of ML models that can be trained to predict as well as make decisions (Woldaregay *et al*., 2019). Whereas many tasks have been performed using deep learning models in medical imaging, such tasks have been achieved using traditional methods (Haskins *et al*., 2020), among them, classification (Yao *et al*., 2020), detection, and segmentation (Lea *et al*., 2017). Instead of viewing big data in a positive light, there are also various challenges that are worth discussing about such models if they are to be deployed in the field of medicine in the near future (Li *et al*., 2020). FL is thus a strategy that enables a healthcare provider and patient to work together and reach set targets (Rieke *et al*., 2020). FL when applied for the case of medical imaging brings with it both shortcomings and challenges (Kairouz *et al*., 2021). Some of them are disscussed below:

1. Due to privacy reasons, it is hard to discover a patient group willing to participate in FL (Pfitzner *et al*., 2021)
2. It is challenging to gather and distribute the data among the participants as it requires servers and client interaction as discussed in (Jiang *et al*., 2020)
3. Healthcare professionals have to enable patients to talk about sensitive issues to them (Aledhari *et al*., 2020). Collaboration with a patient may also be stagnant due to the influence of culture
4. There is a risk that communication between clients and servers that contains medical data may be intercepted illegally by unauthorized parties (Ma *et al*., 2020)

Communications and Technologies are particularly required to be able to consistently interchange information in both the client (or client-side), and the server back and forth, FL may be more expensive in terms of communication costs than the ordinary meeting with eye-ball persons (Pang *et al*., 2021)

FL for Medical Imaging (FLMI) is one possible fix for these challenges (Ng *et al*., 2021). It is a approach that employs Web based platform with the aim of facilitating exchange of data and synergetic work among researchers studying alike populations or diseases (Nguyen *et al*., 2023) and for the FLMI dynamically shared patient's record files, they are able to work together and make certain about the focus of their research and share any patient records for clinical study or research aim (Guo *et al*., 2021). In the absence of such research data from various sources, this strategy would not have been conceivable and has led to a number of important land mark discoveries (Terrail *et al*., 2021). Within the framework of medical domains, among the challenges faced during federated learning are the following:

1. Data security and privacy: HIPAA and other laws are looking towards machine learning tools must be complemented with ensuring privacy and security of medical imaging data. The process of federated learning requires collaboration among several firms and responsiveness with regards to data sharing, which can possibly take time to realize (Xu *et al*., 2021)

2. Data heterogeneity may be: It may prove to be rather complex to design a single system which would work with data from all medical imaging documents since there are bound to be discrepancies in the medical imaging data within different centers and different machines (Prevedello *et al*., 2019)
3. Limited data availability: Such a network can enhance the effectiveness of a federated learning model but nonetheless is likely not to be achieved since a number of hospitals that can adapt the model is few (Pandl *et al*., 2022)
4. Network constraints: Additionally, participants in federated learning and share local models a reliable fast network access is essential in order for them to communicate updates to each other or share data. This might pose a challenge in applying it to remote or developing regions (Foley *et al*., 2022)
5. Alignment of incentives: There must be an incentives framework which defines the scope of cooperation between different entities targeting federated learning (Wang *et al*., 2022b)

FL Frameworks for Cancer Analysis

Current and ongoing cases suggest that several FL frameworks can help enterprises in the actual adoption of an AI-enabled software for conducting business. For examples see Apache-Spark-TF (Guo *et al*., 2018), TensorFlow FL Toolkit (Yang *et al*., 2019), and Apache Hadoop distributed file system (Patil *et al*., 2019). Also, the flt-toolkit was developed by google. Companies, in turn, use this toolkit in order to adapt software to their specific needs (Mothukuri *et al*., 2021). Making use of international agencies' data and the use of an open system, Geleijnse *et al*. (2020) created a framework for oral cavity cancer that made it quick and easy to perform local data trawls across multiple sites. Carpov *et al*. (2022) in work published on 2022, proposed a multiparty computation architecture, GenoPPML, that supports FL and incorporates multisided computation.

In addition to protecting privacy by methods already cited above, for genomics data regression homomorphic encryption and differential privacy are put in use. Matschinske *et al*. (2021) showed a framework which can be used more widely than expected and for many more aims. "Marketplace" strategy is employed in a secure multiparty compute system, whereby FL enables third party applications to utilize infrastructure and other computational capabilities. Carrying out a computational project focused on cancer oriented study incorporating analisys Kaplan-Mayer, data normalizing within a common structure, and accelerating local data research with an open system (Chowdhury *et al*., 2021).

Elayan *et al*. (2021); Banerjee *et al*. (2020) proposed a framework to assist in the training of skin lesion images, using IoT base devices. They utilized FL and avoided looking for large, labeled data by making use of transfer learning (He *et al*., 2020). The Joint Imaging Platform (JIP) has been created by the German National Cancer Center in order to facilitate multiclinical trials improving methods of the tumor treatment and visualization (Scherer *et al*., 2020).

Use of FL in Medical Image Analysis

Due to security barriers experienced by patients, FL has become increasingly popular in medical imaging over the years (Degan *et al*., 2022). It is a subset of machine learning where a model is trained without data sharing (Wang and Tsai, 2022). This is particularly beneficial for medical imaging in that it ensures that data secrecy is maintained and that the data sharing is only limited to the patient's consent (Nguyen *et al*., 2023) This has been used in a so-called descretered image and in processes such as image processing in classification (Agrawal *et al*., 2022) and in segmentation (Gupta and Alam, 2022) tasks. FL has many pros and is a powerful instrument in the fight of penetrating privacy issues (Ouadrhiri and Abdelhadi., 2022). Federated Disentanglement (FedDis), introduced by Bercea *et al*. (2021), is a novel disentangled methodology that allows only the parameters of the model to be exchanged between the clients.

According to Bercea *et al*. (2022), this disentanglement technique operates under the supposition that brain MRI pictures from many institutions have the same anatomical structure and that sharing shape knowledge will aid in anomaly detection.

Model of normal anatomy using actual data from 623 individuals from multiple institutions (OASIS, ADNI) in a privacy-preserving manner to abnormal segment regions. To demonstrate superior performance on real pathological datasets containing 109 patients, the FedDis method outperforms auto-encoders by 42% and federated approaches by 11%.

Yi *et al*. (2020) introduced an SU-Net approach for brain tumor segmentation. It comprises an inception module and a dense block in U-Net to improve information reusing. Evaluate SU-Net (FL model) on the LGG for 'brain MRI segmentation. SU-Net outperforms the baselines in a federated setting. It achieved a 99.7% AUC and a 78.5% DSC, significantly higher than the state-of-the-art deeplabv3+ model, which measures classification accuracy on medical images (DSC is a dice similarity coefficient that measures segmentation accuracy). The concept of data sharing across many cloud platforms will aid third-party players in employing varied big-data analytical approaches. This would allow for the introduction of value-added services such as providing healthcare services to clients through the collection of medical data from multiple facilities. Apart from its numerous applications, data sharing makes major contributions to modern human existence (Maddikunta *et al*., 2022).

Bdair *et al*. (2021) proposed FedPerl, a semi-supervised FL approach, to construct a community and urge its members to share their information by leveraging peer learning. The improvement in the performance of FedPerl compared to the baselines and the state-of-the-art SSFL is 15.8 and 1.8%, respectively. Samanta *et al*. (2022) used FL with a single model to identify head and neck cancer, lung cancer, and lymphoma from 18F-FDG PET/CT scans. Furthermore, compared with Centralized Learning (CL). The conventional averaging method for combining models was more resistant to outliers than the coordinate-wise median approach (Balaji *et al*., 2021). Furthermore, PET/CT images from 8 centers to investigate disease diversity and scanner variation. Experienced neurologists participated in the study to evaluate PET/CT scans of 998 patients (Czernin *et al*., 2017). A training round lasted 100 epochs (100 epochs/round). To train the models, a centralized/FedAvg/CoMed approach was used (100 epochs/round). The ROC curve area was 0.934/0.937/0.950 for lymphoma, 0.988/0.988/0.992 for lung cancer, and 0.979/0.979/0.987 for head and neck cancer cases (Samanta *et al*., 2022). Wicaksana *et al*. (2022) proposed FL (CusFL); a global model is aggregated into client-specific models for training in each iteration. CusFL provides each client with beneficial knowledge from the federated model to enhance their model by learning from it. CusFL achieves superior performance using two key strategies: (1) Features are aligned for the federated model using only feature extraction layers and (2) The federated feature extractor guides the training of each private model. Later, assessed CusFL on a multi-source medical image dataset to identify critical prostate cancer and classify skin lesions. The comparison table for medical imaging with FL techniques is given in Table (1).

In this table, multiple FL approaches are compared and a few different datasets, types of diseases, FL Approaches, and results based on different factors are analyzed to assess the effectiveness of each FL method. After a comprehensive assessment, it is determined that FL techniques are widely adopted and provide effective results when used to train massive amounts of data from several institutes without centralizing the data, which is a suitable privacy-preservation approach.

Table 1: Comparison table of federated learning approaches for medical imaging. A couple of factors are used to see the performance of federated learning techniques: Datasets, the latest paper, algorithms and results

Ref. No.	Year	Disease type	FL Approaches	Methods	Datasets	Results
Roth *et al*. (2020)	2020	Breast cancer	Federated Learning for breast density classification	Classification	BI-RADS	45.8% improvement in the model
Muthukrishnan *et al*. (2022)	2022	Breast cancer	MammoDL is proposed to accurately estimate breast PD and Complexity	Detection	HUP and MC	MAE on HUP data is 4.2806 %
Stripelis *et al*. (2021)	2021	Brain tumor	FL framework to predict the age of the person using MRI Images	Prediction	MRI Images	MAE 6.3%
Dayan *et al*. (2021)	2021	COVID -19	FL for predicting future oxygen requirements EMR and X-ray	Prediction	X-ray images from 20 institutes	0.950% sensitivity and 0.882% specificity
Luo and Wu (2022)	2022	Colorectal cancer	FedSLD	Classification	MNIST and CIFAR10	Test accuracy 5.50%
Hwang *et al*. (2023)	2023	Skin lesion cancer	FL with Proximal regularization except local Normalization (FedPxN)	Classification	Electronic health records, Skin cancer images and electrocardiogram	70.06% accuracy
Jiang *et al*. (2022)	2022	Skin lesion cancer	Semi-supervised FL (imFed-Semi)	Detection	25,000 CT slices and 10,015 dermoscopy images	7.61% and 4.69% accuracy
Pennisi *et al*. (2024)	2024	Tuberculosis and melanoma	Decentralized distributed learning	Classification	Montgomery Country and Shehzhen Hospital X-rays Sets	0.792% accuracy with 8 nodes for IID data and 0.716% for nonsen-IID data
Shiri *et al*. (2022)	2022	Head and neck cancer	Decentralized Federated Deep Transformer Learning Algorithm	Segmentation	220 Clinical PET/CT images	Errors less than 5% for SUVmax and SUVmean
Bernecker *et al*. (2022)	2022	Liver cancer	FedNorm: Modality-Based Normalization in FL	Segmentation	CT and MRI images of 428 patients	Dice per patient scores 0.961
Kalendralis *et al*. (2022)	2022	Head and neck cancer	Dysphagia dose response model validation	Detection	Head and Neck cancer patients	AUC 0.83
Hansen *et al*. (2022)	2022	Larynx cancer	Open-source distributed learning	Prediction	1745 patients	C-index 0.74 and 0.70 for two centers
Kakka *et al*. (2022)	2022	Chest diseases	Six distinct transfer-learning approaches	Detection and Classification	112,120 chest x-ray images from NIH	97.71% accuracy
Mamun *et al*. (2022)	2022	Lung cancer	Ensemble learning techniques	Prediction	Survey dataset of 309 people	94.42% accuracy
Islam *et al*. (2023)	2023	Brain tumor	FL and CNN Ensemble Architectures	Classification	MRI images	96.68% accuracy
Yi *et al*. (2020)	2020	Brain tumor	Aggregation logic in FL framework	Segmentation	341 subjects	Dice scores 0.874, 0.773 and 0.721
Mahlool and Abed (2022)	2022	Brain tumor	Aggregation Model in FL environment	Classification	MRI Images	98% accuracy
Tuladhar *et al*. (2022)	2022	Brain tumor	FL using Variable Local Training	Segmentation	MRI Images	Average DSC score 0.685
Pati *et al*. (2022)	2022	Brain tumor	FL for Rate Cancer Boundary	Detection	MRI Images	33% improvement over a publicity trained model
Pati *et al*. (2022)	2022	Skin cancer	Integrated strategy based many-objective evolutionary algorithm (MaOEA-IS)	Detection	ISIC-2018	Comparison with five algorithms
Lan *et al*. (2022)	2022	COVID -19	FL for COVID-19 Non-IID	Detection	X-ray images	84.4% accuracy
Elshabrawy *et al*. (2022)	2022	Prostate cancer	Xception and VGG19 models	Classification	Local dataset	83.76% accuracy

Conclusion

FL has only recently become a popular AI technique. As a result, researchers have only just begun to explore its potential. First, FL can be used in various situations, including small datasets and distributed environments, making it applicable to many businesses and the privacy of health-related sensitive data. Second, this technique can speed up deep learning's training time, which means the detection of disease will be easier and more accurate. Finally, FL aims to reduce model retraining time, which means doctors don't need to wait as long to see results. All in all, FL is a promising technique for boosting medical imaging AI capabilities. To process medical data, hospitals may need GPUs cloud-based storage, and data centers with high computational power and strong internet connection which are not always available in all hospitals. The hospitals are now moving toward FL techniques because their priorities are working on massive medical data as well as privacy. FL offers straightforward and secure data access for institutions. A Federated environment will help achieve good performance and a deep learning model can be trained on a big dataset which mitigates the over-fitting issues.

Abbreviations

ML	Machine Learning
FL	Federated Learning
JIP	Joint Imaging Platform
FedDis	Federated Disentanglement

Declarations

Availability of data and material is not applicable as it is a survey work. Competing interests the authors have no competing interests.

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Author's Contributions

Muhammad Imran Sharif and Mehwish Mehmood: Contributed to conceptualization, investigation, analysis interpretation, and written-original draft preparation.

Md Palash Uddin, Kamran Zahid, Zahid Akhtar, and Sadia Waheed: Contributed to revised, reviewed, edited, and validation.

Ethics

The authors confirm that they will address any ethical issues that may arise post-publication, ensuring transparency and corrective actions if necessary.

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