**FedDropoutAvg**: Generalizable federated learning for histopathology image classification

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*Abstract—* Federated learning (FL) enables collaborative learning of a deep learning model without sharing the data of participating sites. FL in medical image analysis tasks is relatively new and open for enhancements. In this study, we propose FedDropoutAvg, a new federated learning approach for training a generalizable model. The proposed method takes advantage of randomness, both in client selection and also in federated averaging process. We compare FedDropoutAvg to several algorithms in an FL scenario for real-world multi-site histopathology image classification task. We show that with FedDropoutAvg, the final model can achieve performance better than other FL approaches and closer to a classical deep learning model that requires all data to be shared for centralized training. We test the trained models on a large dataset consisting of 1.2 million image tiles from 21 different centers. To evaluate the generalization ability of the proposed approach, we use held-out test sets from centers whose data was used in the FL and for unseen data from other independent centers whose data was not used in the federated training. We show that the proposed approach is more generalizable than other state-of-the-art federated training approaches. To the best of our knowledge, ours is the first study to use a randomized client and local model parameter selection procedure in a federated setting for a medical image analysis task.

**Index Terms—** Federated Learning, Model Aggregation, Convolutional Neural Networks, Computational Pathology

I. INTRODUCTION

In recent years, deep learning methods have shown success in many different tasks including those in computational pathology [1]. A major drawback to these approaches is the need for large amounts of data to train the networks. This drawback is even more obstructive in the medical field, as medical data are difficult to access and their sharing may be subject to legal and ethical limitations.

Federated learning (FL) [2, 3] allows to overcome these challenges. While in traditional deep learning approaches, all data is required to be co-located in a central server where model training takes place, in an FL paradigm, each of the multiple decentralized centers holding local data can train the model on their own servers. By enabling training of the deep learning models collaboratively without exchanging the datasets, FL offers a solution to data ownership and governance issues [4]. Existing FL methods comprise of several rounds of local training and federal aggregation steps. In each round of the federated training process, each data-holder trains a model for some number of epochs on their local dataset. The local data-holders then send their trained models to a central server for model aggregation. The aggregated model is sent back to the data-holders for further training rounds.

Model aggregation is an important step for the overall performance. The most common method of model aggregation in existing FL studies is Federated Averaging (FedAvg) [3]. FedAvg is weighted averaging of local model parameters (the gradients) to obtain a global model at each round. The weights in this case are determined based on the number of training samples of each local data-holder. Li et al. [5] argued that local models are often substantially different from global models because of the heterogeneous and imbalanced nature of the datasets. Therefore, they proposed FedProx, which contained a proximal term in the loss function to restrict the effects of local training and prevent divergence from the global model parameters.

Study of FL in the area of medical image analysis is relatively new. Existing FL approaches in the medical imaging domain have focused on specific tasks including: analysis of brain imaging data [6, 7, 8], CT hemorhage segmentation [12], breast density classification in mammography data [13], pancreas segmentation in abdominal CT images [14] and classification of histopathology images [15, 16]. Most of the FL studies in medical imaging have employed FedAvg method for model aggregation [6, 7, 8, 9, 10, 11, 13, 14, 15]. Andreux et al. [16] proposed an enhancement for aggregation of batch normalization (BN) layers. Remedios et al. [12] incorporated momentum in the gradient averaging method.

Medical image datasets can be very heterogeneous and unbalanced. Besides being unbalanced in terms of number of samples, the data quality and the diversity of different samples could differ by a large margin. In this case, the approach of FedAvg and FedProx, weighting the contributions of each local model by their data size, may have limitations. Since we cannot know beforehand which private local dataset(s) will generalize better for the test set of another center, measuring the contributions of individual centers and accurately weighting them is not feasible. While local validation set performances could be used to increase the weight of under-performing centers during training, these under-performing centers could have low data-quality and may not be worth
Fig. 1. Workflow diagram of the proposed *FedDropoutAvg* approach. **Training phase:** At the beginning of each training round, *Central Server* sends global model weights to some clients which are randomly selected from all the clients participating in the training. Using the received model, local training takes place at each client on their local datasets. At the end of local training epochs, each *Client* $i$ sends the parameters of their locally trained model to *Central Server*. Then, *Central Server* randomly drops out some of the parameters of the received models and aggregates the models into a global model by averaging. This training process continues for some number of rounds. **Testing phase:** After the federated training is over, *Central Server* sends the final model to independent clients for use on their own test sets, simulating a real life scenario.

learning strongly for the greater good. Therefore, we propose introducing dropout strategies for global model aggregation and clients participating in FL training to mitigate the complexities of learning from imbalanced and heterogeneous datasets from various clients.

In this paper, we propose Federated Dropout Averaging (*FedDropoutAvg*), a new FL aggregation method with the objective of obtaining a global federal model that achieves maximum performance by adjusting dropping out of the parameters of locally trained models before aggregation and also randomly dropping out some clients at each round. Our approach is inspired by FL model training with sensitive user data on mobile devices [2], [3], where thousands of clients participate and several clients may also get dropped out at each training round due to various reasons and constraints like unstable connectivity or efficiency [3], [17], [18], [19]. However, the impact of clients dropping in FL training for medical image analysis tasks remained unexplored.

The proposed federated dropout averaging method for aggregating weights and parameters of deep neural network models trained at different client sites into a federated model is also different from the well-known dropout technique used to drop weights of the neurons during training of standard convolutional neural network by Srivastava *et al.* [20]. We present a comparative evaluation of the proposed method with locally trained models, the model trained in a centralized manner and two major FL model aggregation methods for histopathology image classification. We explore the comparative performance of the different methods on multi-institutional histopathology images datasets using federated models in real-world setting, using not only test data from centers (clients) participating in training but also the held-out test data from completely different centers.

To be more specific, our work makes the following novel contributions:

- We present *FedDropoutAvg*, a novel FL approach for federated training of deep learning models for histopathological image classification.
- We demonstrate the feasibility and superiority of our method using a large multi-site dataset. The data used in this study consists of 1.2 million images from 21 different centers. The individual datasets of these centers are imbalanced in terms of number of samples, patients, and number of positive and negative image patches and contain significant variation in the image data (color, brightness, focus) – the so-called domain shift, as can be observed in Figure 2 – due to variations in scanning and staining parameters.
- We show that our proposed approach outperforms previous federated strategies not only on the held-out test data of centers participated in training, but also on the data of independent centers whose data was not used in the training process at all.
II. MATERIALS AND METHODS

In this section, we introduce the dataset and methods used in this study. An overall view of the proposed FedDropoutAvg method can be seen in Fig. 1.

A. The Dataset

1) TCGA CRC-DX Dataset: The dataset used in this study comprises of multi-gigapixel whole-slide images (WSIs) of 599 diagnostic slides from 591 colorectal cancer (CRC) patients contributed from 36 different centers to The Cancer Genome Atlas (TCGA) project. We used the Otsu thresholding [21] to extract tissue region from each slide. The non-overlapping square tiles of size $512 \times 512$ were extracted from the segmented tissue region at $20\times$ magnification.

2) Tumor Segmentation: For tumor segmentation, we fine-tuned ResNet18 [22] pre-trained on ImageNet to distinguish between tumor and non-tumor tiles of each slide for the FL experiments. The total of 35436 tiles are extracted from seven randomly picked TCGA slides and two publicly available data sets [23], [24]. Seventy percent of the data (24843 tiles) split for training, fifteen percent each for validation (5380 tiles), and held-out test set (5213 tiles with 2493 non-tumor tiles and 2720 tumor tiles). The network distinguished the tiles of the unseen test set belonging to the tumor and non-tumor classes with an accuracy of 99% [25]. We used this trained network to separate the tumor and non-tumor tiles from the entire TCGA cohort.

3) Data Collection for FL Experiments: Using the tiles and their labels as described above, we initially collected a multi-institutional dataset containing samples from 36 different centers. We have excluded centers contributing data of fewer than five patients from this study and randomly divided the dataset of the remaining 21 centers into federating training (11 centers, Local Sets) and independent test set (10 centers, Independent Sets). The data of Local Sets is patients-wise split into training, validation, and test sets (50%, 10%, 40%), keeping the tiles belonging to the same patient in the same set. Only the training set of Local Sets is used in model training and the validation set of Local Sets is used to select the best model parameters. In federated training, each local model is trained on the corresponding local training set of the clients in the Local Sets. In classical Centralized training, a single model is trained on the union of the training sets of the clients’ data. Test sets of the clients in the Local Sets and all of the data of the clients in the Independent Sets have been used for evaluation purposes. More details are shown in Table I.

B. Federated Dropout Averaging (FedDropoutAvg)

1) Dropping out model weights before aggregation: Our proposed method is based on FedAvg proposed by [3] which is the most popular method used for model aggregation in federated systems. In FedAvg method, in each federated round $t$, global model parameters $\theta^{t+1}$ are calculated as follows:

$$\theta^{t+1} = \sum_{i=1}^{C} \alpha_i \theta_i^t$$

(1)

Here, $\alpha_i \geq 0$ is the contribution weight of each client $i$, while there are $C$ clients joining the federated training process.

In standard federated averaging, $\alpha_i$ is calculated as the proportion of number of data samples $N_i$ of each client $i$ to total number of samples of all clients participated in training $N^{(t)}$. 
TABLE I
Number of patients \((n_i)\), number of tumor \((N_{t,i}^j)\) and non-tumor \((N_{nt,i}^j)\) image patches (each patch being 512×512 pixels) per center \((\text{client } i)\) and total number of patches \((N)\) from the TCGA-CRC-DX dataset used in the training (TR), validation (VAL) and test (TS) sets. Training data from centers “CM” through “AA” used for training, their hold-out test sets and data from “QG” through “AD” used for testing. In the 3-fold experiments, at each fold, data from 7 different centers used for testing.

| All Centers | CM | AY | A6 | DY | AF | CK | DC | G4 | AG | AH | AA | TR | n | N_{nt,i}^j | N_{t,i}^j | VAL | n | N_{nt,i}^j | N_{t,i}^j | TS | n | N_{nt,i}^j | N_{t,i}^j |
|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|------|------|-----|----|------|------|----|----|------|------|
| N_{nt}^j   | 53.5K | 4.7K | 13.9K | 6.9K | 27.3K | 15.2K | 54.2K | 5.4K | 13.9K | 23.7K | 8.5K | 3.8K | 30.9K | 12.3K | 24.0K | 1.6K | 3.8K | 12.3K | 34.0K | 12.3K | 2.1K |
| N_{t}^j    | 27.0K | 5.9K | 11.9K | 5.4K | 9.2K | 11.2K | 14.6K | 19.4K | 1.0K | 1.6K | 19.4K | 4.7K | 12.0K | 7.1K | 13.4K | 5.8K | 9.6K | 5.0K | 7.1K | 6.0K | 2.5K |
| N_{nt}^j   | 15.4K | 0.2K | 16.6K | 1.6K | 1.3K | 37.2K | 3.1K | 3.5K | 2.7K | 37.2K | 6.5K | 11.4K | 8.1K | 12.2K | 12.2K | 12.2K | 12.2K | 12.2K | 12.2K | 12.2K | 12.2K |
| N_{t}^j    | 6.8K | 1.9K | 2.3K | 1.3K | 0.3K | 4.2K | 5.6K | 3.5K | 4.3K | 1.0K | 11.4K | 2.8K | 3.2K | 2.4K | 3.3K | 3.9K | 1.7K | 3.5K | 399 | 3.5K | 676 |

\[
\alpha_i = \frac{N_i}{N} \quad \text{where} \quad N = \sum_{i=1}^{C} N_i
\]

In the FedDropoutAvg method, we propose to dropout some of the weights from each client model \(\theta_i\) before aggregation and adjust the contribution weights accordingly. Here, we define a new parameter Federated Dropout Rate \(fdr\), where \(fdr = 0\) is same as the standard FedAvg. In our experimental settings, the best value for this parameter is selected as \(fdr = 0.3\) (when \(cdr = 0.2\)). At the end of each round, we create random masks for each client model \(\theta_i\), and use those masks to select the model parameters (weights) which will be included in the aggregation process.

For a more formal explanation, let parameter \(p_{k,l,i}^t\) be any parameter (weights or biases) of any layer \(l\) at index \(k\) in model \(\theta_i\). Then, \(p_{k,l,i}^{t+1}\), the parameter at the same index of the aggregated global model will be calculated as follows:

\[
p_{k,l,i}^{t+1} = \sum_{i=1}^{C} \alpha_{k,l,i}^t p_{k,l,i}^t
\]

where, \(\alpha_{k,l,i}^t\) is the contribution weight of each client parameter \(p_{k,l,i}^t\) and obtained as follows:

\[
\alpha_{k,l,i}^t = \frac{N_{t,k} R_{k,i}^t}{N_{nt,k}^t} \quad \text{where} \quad N_{t,k}^t = \sum_{i=1}^{C} N_i R_{k,i}^t
\]

Here, \(N_{nt,k}^t\) indicates the total number of data samples of all the clients whose parameter at layer \(l\) at index \(k\) are not dropped out from aggregation at the end of round \(t\).

The \(R_{k,l,i}^t\) value in the calculation is a random Boolean value \((0\ or\ 1)\) which is obtained using the newly defined \(fdr\). Where RandomUniform() draws a value from a uniform distribution over the half-open interval \([0, 1)\):

\[
R_{k,l,i}^t = (\text{RandomUniform}() > fdr)
\]

2) Client dropout: At each federated round, a random subset of clients are selected to participate in model training at that round. We have defined a new parameter Client Dropout Rate \((cdr)\) which modifies the the number of clients selected at each round. For a specific \(cdr\), number of random clients selected at each round is constant. Please note that, for the case where \(cdr = 0\), all of the clients will participate at each training round.

C. Model

We have used ResNet18 [22] model with group normalization (GN) [26] layers instead of BN layers, as the GN layers are known to be more successful in decentralized machine learning settings [27].

III. EXPERIMENTS AND RESULTS

A. Implementation and Training

Local models and federated models are locally trained on the training data of clients in the Local Sets. We have also trained the centralized model for comparison which is trained on data from all the training sets. For evaluation, we have compared the proposed FedDropoutAvg method with FedAvg and FedProx methods.

All of the models are trained from scratch on GPU for each comparison. For model training, we used class-weighted binary cross-entropy loss and SGD optimizer with initial learning rate 0.1, momentum 0.9 and weight decay 0.0001, with the learning rate halved after every 2 epochs. We have trained federated models (FedAvg, FedProx and proposed FedDropoutAvg) for 20 rounds (one epoch per round) and selected the best model based on total cross-entropy loss on local validation sets. Similarly, local models and centralized model are trained for 20 epochs and models from the epochs with the best validation loss have been selected.

FedAvg and FedProx models are trained in same settings with the proposed FedDropoutAvg model. The proposed FedDropoutAvg model is same with FedAvg model when \(cdr = 0\)
and fdr = 0. For FedDropoutAvg model, the best cdr and fdr parameters are selected on validation set as 0.2 and 0.3, based on a grid search on cdr ∈ {0, 0.1, 0.2, 0.4} and fdr ∈ {0, 0.1, 0.2, 0.3, 0.4}. FedProx method has a parameter (µ) which adjusts the effect of the proximal term on the loss function. This parameter is selected as 0.01 after a grid search from 0.5, 0.1, 0.01, 0.001 based on the performance on the validation set. For the implementation of the models and methods, we used PyTorch.

B. Experimental Results

In this section, we present results of comparative analysis of our method with other FL methods, local training and centralized training approaches. We also analyze the effect of different cdr and fdr parameters on the performance.

1) Limitations of local models: The F1 score of each locally trained model (rows) on each local held-out test set and on the independent test set given as heatmaps in Fig. 3 and Fig. 4. Comparing federated models (Fig. 5) with locally trained models, we observe that, on the individual local test sets, the federated methods, especially our proposed method, perform better than most of the locally trained models on the held-out test set of that center. This strengthens the motivation to put federated learning into practise. Comparing locally trained models with each other, we see that some of the locally trained models are indeed do best on the test set of the same client they are trained on (CM, A6, DY, G4, AA). Surprisingly we observe this is not the case for majority of them. For example, we see that the model locally trained on the training data of DC give the best F1 results compared to other local models on the test sets of AY and AH. Likewise, among other local models, the locally trained model on A6 is best for AF, CK and DC; and locally trained model on AA is best for AG. These results point to complexity of the underlying relationships between the different local models. They also supports our initial motivation about not being able to measure the individual contributions of each local dataset.
without sharing the datasets.

2) Experimental analysis: To compare different approaches, F1 scores and AUROC values are calculated for each comparison model on 21 different test sets (held-out data of training centers and data of independent centers).

In Table II, the average performance of the centralized and federated approaches is shown. In the table, performance is given as the mean and the standard deviation of the F1 metric on the local and independent test sets. As expected, the Centralized model, which is trained on all of the training data in a classical way, gives the best mean F1 score among all of the comparison models. Compared to other federated approaches, proposed FedDropoutAvg model (with cdr = 0.2 and fdr = 0.3) produced the most competitive result with the Centralized model.

In Fig. 5 and Fig. 6, we see the performance comparison of federated approaches on the individual local test sets and for individual independent sets. In these results, we see that proposed FedDropoutAvg method consistently better than other federated approaches on these individual testing sets. This success of our proposed approach is attributed to the proposed client dropout and clients’ model weights drop-out mechanism. Our approach indeed helps avoiding over-fitting to individual local datasets.

In the held-out test sets of center AY and AA, the ratio of tumor vs non-tumor tiles is very imbalanced (Table I). This could be the reason why the F1 performances of all of the federated approaches on the test sets of these centers are lower compared to other centers (Fig. 5). Although our approach still has better performance than the other federated models.

3) 3-fold experimental analysis: We also performed 3-fold cross validation experiments. We divided the 21 centers into three splits, where each split contains 7 centers. At each fold, the centers in the two splits have participated in training while the centers in the remaining one split are used as the independent test sets. Similar to the previous experiments, at each fold, we have calculated the performance metrics from the independent centers and from the held-out test sets of the centers participated in training. The results of these experiments can be seen in Table III. These results further confirm that our proposed approach is superior than other federated approaches in terms of F1 and AUC values on both local and independent test sets.

4) Experimental analysis for training with different cdr and fdr parameters: To understand the effects of cdr and fdr parameters, we also trained the proposed FedDropoutAvg method with different parameters. Keeping in mind that the model federatively trained with cdr = 0 and fdr = 0 corresponds to the FedAvg method in the literature, we see that selecting greater than zero values for both of the parameters provides gains in F1 score.

In Fig. 7(a), performance results of models trained with different fdr parameters when cdr parameter is equal to 0 (as in FedAvg) and equal to 0.2 (as the reported model here) can be seen. Here, we see that the models trained with cdr = 0.2 give close or better results than their counterparts (cdr = 0).

Likewise, in Fig. 7(b), performance results of models trained with different cdr parameters when fdr parameter is equal to 0 (as in FedAvg) and equal to 0.3 (as the reported model here) are presented. Here, we also see that the models trained with fdr = 0.3 give better results than their counterparts (fdr = 0).

Additionally, in Fig. 7(b), we can argue that in standard federated learning (i.e., when we do not use federated dropout,
Fig. 6. Performance (AUROC) of the federated approaches on (a) the held-out test sets of the centers participated in training, (b) the datasets of the independent test centers (Note that these centers did not participate in the training of the models).

5) Qualitative analysis on WSI level: In Fig. 8, qualitative results of different methods on WSI level are presented with respective slide-level F1 scores. Centralized, federated and local training methods are compared. The WSIs in this figure are from four different independent testing centers (AD, F4, NH, D5), thus the models are not trained on these centers’ dataset. The best local models are selected based on comparison of all of the locally trained models by the slide-level F1 metrics. For all of the WSIs, our proposed method has given better results than other federated approaches (FedAvg, FedProx) both qualitatively and in terms of F1 score. In the last three columns, we see that best of the locally trained models give better results than federated approaches. The results in the last column can be regarded as a fail case for all of the federated models, although it should be noted that our model still gives better results.

IV. DISCUSSION AND FUTURE DIRECTIONS

In this study, we demonstrated FedDropoutAvg method as a better way to train models with federated learning for histopathological image analysis tasks. In the application we presented, FedDropoutAvg achieved closer performance to the conventional training where all of the data is centralized in a data lake, compared to other major federated learning approaches. We think that our strategy will allow us to achieve the goal of training better and more robust models with higher clinical usefulness while maintaining the privacy of the data via federated learning.

The dropout method in the literature [20] is a generic technique to reduce over-fitting while training a routine neural network and it is different than our approach in several ways. Firstly, it is to be used in a single neural network training and not for FL settings. Our approach is proposed for adapting model aggregation step of FL. Also, in this method only hidden layer model weight parameters are dropped-out at training time. In our proposed method, all of the model parameters might be dropped-out before federated aggregation step, including the ones in the first and final layers, and also the bias parameters. Also, the obtained aggregated global model is used both for further training rounds and/or testing.

There have been other FL studies inspired by the dropout method [28], [29]. Namely, “Federated Dropout” [28] and “Adaptive Federated Dropout” [29]. The main goal of both of these approaches is to increase communication efficiency by decreasing the model size to be sent and received by the local clients (mobile devices). Since those studies are for FL in mobile devices, communication efficiency is an important
Fig. 8. Example qualitative results of different methods on WSI level. **First row**: regions of interest (ROI) in four WSIs from different independent centers (respectively: AD, F4, NH, D5; original slide names are written on top of the images). **Second row**: ground-truth segmentation masks. **Other rows**: binary segmentation masks of different methods overlaid on images, red areas indicating “tumor”, blue areas indicating “nontumor” predictions. Respective slide-level F1 metrics are given below each result. For the last row, best local models are selected based on comparison of all of the locally trained models by the slide-level F1 metrics; shown in parantheses are the center IDs of selected local models. All of the WSIs are from independent test sets and the presented methods are not trained on the datasets of the centers these WSIs belong to.
aspect due to the large number of devices involved in the training. In these approaches, each local client trains a smaller model (a submodel of the global model) to reduce model size and update size, while the server has the whole global model. Clients train a selected subset of the global model, and it is either a random subset \( [28] \) or dynamically selected subset \([29]\). Then, the server maps and reunites those smaller locally trained models into the global model. Differently than these approaches, we propose to train the same whole global model architecture locally at each client, achieving better trained local models and a much more flexible drop-out application at aggregation time.

Although there are other FL optimization methods in the literature, those are usually different additions to the FedAvg method. Because of this, in this study, we only used the major ones for comparison. We strongly believe that our proposed approach can easily be combined with other additional optimization techniques (e.g., gradient averaging with momentum of \( [12] \)).

As an added benefit, our proposed method could provide gains in both communication efficiency and the total amount of computation time for a real-world histopathology image analysis system. For example, when \( cdr = 0.2 \), only 8 random clients participate at each round out of 11 clients. As a result, at each round, computation will only take place at the selected subset of clients. The clients who are not selected do not need to communicate with the server at the end of the round, providing a straightforward way to increase communication efficiency. Also, total amount of computation time will be decreased, since it is proportional to total amount of data of the selected clients. We did not provide an analysis of this aspect since the amount of data of each local training client is very heterogeneous in our dataset. In the future, additional multiple experiments can be done to understand computational efficiency of the proposed method.

We acknowledge that due to the client (center) drop out mechanism of the FedDropoutAvg, it might be difficult or even impossible to deploy this method for a setting with a small number of participating centers, which is usually the case for medical image analysis studies. However, we believe that FedDropoutAvg could significantly improve the performance of the final models of future studies which have high number of centers participating.

V. CONCLUSIONS

Federated learning can help different institutions contribute to the training of powerful models without requiring any training data to be shared. In this paper, we proposed FedDropoutAvg and explored this federated training approach for real-world multi-site histopathology image classification and compared it with various existing federated learning methods. We evaluated the trained models on an independent test set of clients which have not participated in the training process. We showed that by using the proposed federated learning method, it is possible to achieve a classification performance comparable to a centralized model that requires data from all the clients used for training the model. In this study, we did not examine the privacy limitations of the proposed approach. We did not consider the data leakage from the model parameters if someone attempts to reconstruct the data using the model parameters exchanged during the federated training (i.e., a model inversion attack). In future, the effects of the proposed approach on privacy and combination of the proposed approach with different privacy-preserving techniques can be examined. Model aggregation is a critical piece of the FL paradigm and the improvement in performance and generalization ability of this new federated aggregation method has rich potential for usage in the future FL models.

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