Advances in Pneumonia Detection: A Comprehensive Investigation of Federated Learning and Deep Learning-Based Approaches

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Abstract: In the realm of healthcare, federated learning (FL) emerges as a promising solution to address the challenges of data silos and privacy concerns in medical diagnosis. This paper delves into the application of FL in the context of pneumonia detection, with a focus on leveraging convolutional neural networks (CNNs) within a federated learning framework. The study provides a comprehensive overview of the potential of FL in processing sensitive medical data, particularly in enhancing the accuracy of pneumonia detection. By employing deep learning models such as Convolutional Neural Networks, VGG-16, ResNet50, and DenseNet121, the research demonstrates significant improvements in detection accuracy. Furthermore, the paper explores the integration of ensemble learning with federated learning, highlighting its potential to augment the generalization capabilities of models while bolstering data privacy protection. Despite the promising results, the study also identifies several key challenges that need to be addressed, including issues related to data quality, communication overhead, evolving healthcare regulations, and the need for standardization in the application of federated learning in healthcare settings. Overall, this paper underscores the potential of federated learning in revolutionizing the diagnosis of pneumonia while ensuring the protection of patient privacy and data security.

1 INTRODUCTION

In today's healthcare sector, accurate and timely detection of pneumonia is crucial for enhancing patient recovery rates and reducing disease transmission. As a principal cause of mortality globally among various age groups, especially for young and old (Hespanhol & Bárbara, 2019; Ngari et al., 2017), the urgency for effective pneumonia detection mechanisms has never been more pronounced. With the increasing development of the healthcare industry, a large number of multi-structured patient data from clinical reports, doctor's notes, wearable devices, etc., are being generated every day. The advent of voluminous medical data has led to a significant shift towards leveraging machine learning and Artificial Intelligence (AI) technologies to boost the efficiency and accuracy of pneumonia detection (Ni et al. ,2020). Despite the promise shown by these technologies, their deployment faces substantial hurdles due to data isolation and privacy concerns.

The proliferation of AI in medical diagnostics has showcased the potential of Deep Learning (DL) techniques in interpreting complex medical images (Qiu, 2019; Qiu, 2022), including chest CT scans and X-rays, for pneumonia detection. The COVID-19 pandemic has underscored the critical role of advanced diagnostic tools, with several studies demonstrating the efficacy of DL in enhancing pneumonia detection rates from imaging data (Chen et al., 2020). These advancements highlight the transformative impact of AI on medical diagnostics, offering a glimpse into the potential for more accurate, efficient, and early detection of diseases (Zheng et al., 2021).

However, the majority of this research is confined to datasets within single healthcare institutions, largely due to the sensitive nature of medical data and stringent privacy laws. This limitation restricts the generalizability of AI models, as datasets from a single source may not adequately represent the diverse manifestations of diseases across different populations. Federated Learning (FL) emerges as a

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promising solution to this challenge (Bonawitz et al., 2019). By enabling multiple entities to collaboratively train models without exchanging raw data, FL addresses privacy concerns while tapping into a broader data pool. This approach not only ensures patient privacy but also enhances the model's ability to learn from a diverse set of data representations, potentially increasing its diagnostic accuracy and generalizability.

While the theoretical promise of Federated Learning (FL) in medical AI is well-recognized, practical applications remain relatively unexplored, especially in the context of cross-institutional pneumonia detection. This study aims to analyze the deployment of various FL frameworks for pneumonia detection, with the goal of providing valuable insights and guidance for future applications of FL in this domain.

2 METHOD

2.1 Federated Learning

Federated learning shown in Figure 1 is a paradigm in machine learning that enables multiple participants (which could be institutions or devices) to collaboratively train an algorithmic model without the need for direct data exchange between them (Bonawitz et al., 2019). A global model in the aggregation server is distributed to different local train nodes for training on their respective data. Rather than transferring the data, the weights are exchanged between local nodes and aggregation server. After the local training, local nodes send their trained weights back to the aggregation server. Then the server updates the global model by integrating the trained weight returned by each local training node. Various aggregation algorithms, such as FedAvg (McMahan et al., 2017), Robust Aggregation (Wan & Chen, 2021), SEAR (Zhao et al., 2022), have been widely implemented in practical applications. The updated global model is then sent back to the local train nodes, and the iterative training process continues. This approach demonstrates the unique advantages of federated learning, which effectively protects patient privacy when dealing with data across healthcare organizations (Farkaš, Ciobanu, & Dobre, 2023). During federated learning, different healthcare organizations can jointly contribute to model updates while avoiding the sharing of sensitive patient data. In a task such as pneumonia detection, where data quality and dataset size are critical, federated learning is able to learn across different healthcare organizations, increasing the sources of data. Thus, federated learning can accelerate the development of pneumonia diagnostic techniques while ensuring diagnostic accuracy.

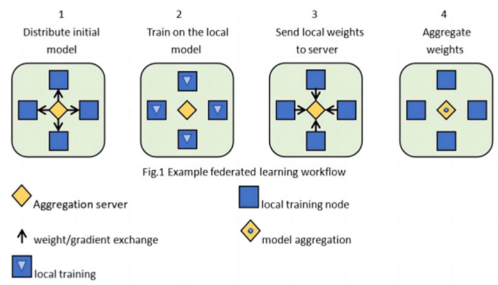

Figure 1: The general workflow of federated learning (Photo/Picture credit: Original).

2.2 Convolutional Neural Networks (CNNs)

Convolutional neural networks are the cornerstone of modern image analysis, especially in the field of medical imaging. Their ability to adaptively learn spatially hierarchical features in images makes them well suited for classification and object detection. In federated learning for pneumonia detection, CNNs play a pivotal role due to their high efficiency in processing image data and extracting relevant features critical for accurate diagnosis (Liu, 2023; Zhang et al., 2021; An, Chen, & Shao, 2024).

2.3 Application in Pneumonia Detection with CNNs in Federated Learning

2.3.1 VGG16

Currently VGG16 have achieved excellent performance in federated learning for pneumonia detection, according to (Farkaş, Ciobanu, and Dobre, 2023), federated learning models of CNNs demonstrated promising results, reaching an accuracy of about 95% in pneumonia detection and effectively protecting data privacy (Farkaš, Ciobanu, & Dobre, 2023). They implemented their model using Keras based on the TensorFlow Federated (TFF) framework and the VGG16 (Wang, 2020) architecture. VGG16 uses a 3x3 convolutional filter (kernel) instead of a larger filter, effectively reducing the number of trainable parameters and enabling efficient feature detection. They also added variety to the dataset through transformations such as horizontal rotation, scaling ranges, and width/height shifts. Through the combination of multiple advanced techniques and models for image preprocessing techniques, a federated learning model based on VGG16 is realized, and the effectiveness of CNN in the federated learning process is verified. However, since the dataset is only derived from children in one hospital, this will limit the generalization ability of the model in other age groups, and this study divides a dataset into ten subsets for simulation of federated learning, which may not be able to realistically simulate the distribution of data in the real world. This study directly addresses the challenge of using machine learning to detect pneumonia while overcoming the barriers of data privacy and computational efficiency.

In the work of (Khan et al., 2021), a federated learning model was proposed. Their dataset has 4, 684 training images and 1, 172 test images classified as either pneumonia or normal. The raw data is processed by the canny filter, which improves the accuracy of the deep learning model by about 10%. The processed data set was split into two parts, which were used to simulate the local data sets of the two hospitals, trained using a federated learning process, The performance of CNN model (using 4 Convolution, Max-Pooling and 2 Dense), ResNet50 model, VGG16 model and AlexNet model is compared. The study evaluated each model based on its training and validation accuracy, global accuracy, precision, recall, F1 score, Cohen's Kappa score, area under the ROC curve, sensitivity, specificity, and construction time.

2.3.2 ResNet-50 and DenseNet121

ResNet-50 and DenseNet are also state-of-the-art model architectures based on CNNs. DenseNet improves the traditional CNN architecture by introducing a dense connectivity mechanism, which enhances the transfer of features and reduces the number of parameters to ensure that the information is maximally utilized in the network (Nithya, MohanaSundaram, & Santhosh, 2023; Huang, Liu, Van Der Maaten, & Weinberger, 2017).

According to a study by (Kareem et al., 2023), a federated learning framework was developed to enhance pneumonia image detection using distributed data across different institutions, it enables different healthcare organizations and hospitals to participate in the training of the model together. This study deployed four virtual devices within the framework, each representing a training entity, and the models were trained independently on their respective devices, ensuring localized data processing and privacy protection. The study began with the collection of a dataset containing both pneumonia and non-pneumonia images, followed by a series of standardized data preprocessing operations and deep dives into the data features through exploratory data analysis (EDA). Once the data preprocessing was completed, the data were divided into 70% training set, 20% validation set and 10% test set. In addition, the training set data was equally distributed to four virtual devices, where the model hyperparameters and optimizer were tuned and added.

In this study, various CNN models including Resnet-50, AlexNet, Densenet, Inception, and VGG.19 were employed for experiments under a joint learning framework, involving 20 training cycles across four virtual clients. Despite CNNs' advantages in scalability and overfitting prevention with large datasets, the study observed a notable discrepancy in performance when models were applied individually versus in a joint learning scenario. Particularly, the aggregated performance in joint learning did not meet expectations, notably in disease classification tasks. DenseNet and ResNet-50 showed comparable performance in joint learning, with DenseNet slightly underperforming alone, suggesting data dispersion's negative impact. AlexNet and Inception faced significant performance drops, indicating issues with data adaptability and model aggregation, respectively. VGG.19 maintained relative performance, albeit lower than solo use. Conversely, ResNet-50 exhibited minimal performance decline, underscoring its robustness and suitability for federated learning in pneumonia detection models.

2.3.3 Ensemble Learning

The ensemble learning approach improves the predictive performance of a model by combining multiple learning algorithms. Its core idea is to overcome the limitations of a single model by aggregating the prediction results of multiple models, and to reduce the overall prediction error by utilizing the strong points of multiple models (Sulistya, Bangun, & Tyas, 2023). In convolutional neural network modeling, using an integration strategy provides results superior to any single model.

In convolutional neural network modeling, using an ensemble strategy provides results superior to any single model (Mabrouk et al., 2022). In the 2023 study, Mabrouk et al. explore an ensemble federated learning approach designed to facilitate collaborative pneumonia diagnosis. This methodology integrates multiple learning algorithms and distributed data sources, enabling various institutions to share learning models instead of raw data. This approach enhances pneumonia diagnosis accuracy and efficiency while safeguarding privacy (Mabrouk, Redondo, Abd Elaziz, & Kayed, 2023).

The research adopts a two-phase strategy, starting with independent learning at the local node (hospital) level using multiple Convolutional Neural Network (CNN) models, followed by coordinating and ensembling these learnings at the global level through a federated learning framework, aiming to build a more robust and accurate globally integrated model (GEL) while ensuring that the data privacy of individual nodes is protected.

In a two-phase approach to improve pneumonia diagnosis, local nodes (hospitals) first employ eight pre-trained CNN models, including densenet169, mobilenetv2, xception, inceptionv3, resnet50, vgg16, densenet121, and resnet152v2, for Local Ensemble Learning (LEL). These models, initially trained on ImageNet for broad image recognition, are further tailored to chest x-ray datasets at each node. Based on performance, primarily accuracy, each node selects its top two models to create an LEL model.

In the subsequent federated learning phase, nodes transmit their LEL models to a central server, which aggregates them into a Global Ensemble Learning (GEL) model. This federated approach facilitates the integration and sharing of learned knowledge across nodes without exposing sensitive data. The GEL model is then circulated back to nodes for further refinement and validation, in an iterative process aimed at optimizing the global model's performance, thereby enhancing the accuracy and efficiency of pneumonia diagnostics while maintaining data privacy.

3 DISCUSSIONS

In exploring the application of FL in pneumonia image detection, many studies not only reveal its great potential in protecting patient privacy and facilitating cross-institutional collaboration, but also must confront the multiple challenges and limitations in applying this technology to real-world healthcare scenarios.

Data quality plays a crucial role in sharing models across hospitals and healthcare organizations (Mashoufi, Ayatollahi, Khorasani-Zavareh, & Boni, 2022). If there are data quality issues in the participants, such as corrupted or inaccurate data, it will directly affect the training effect and performance of the machine learning models. This data heterogeneity problem requires us to perform strict data quality control before data preprocessing and model training to ensure the effectiveness of model training. At the same time, the establishment of a unified standard Healthcare Data Warehouse may be an effective solution (Berndt, Fisher, Hevner, & Studnicki, 2001), the establishment of a standardized data warehouse to improve data quality, ensure data security and privacy, and ensure that data can effectively support decision making, should be able to help federated learning data quality.

Communication overhead is also a major challenge for real-time implementation of FL frameworks. The amount of communication required for model updating and synchronization among collaborating organizations with large-scale datasets can be huge, especially in bandwidth-constrained environments, which may negatively affect the efficiency and performance of model training. Therefore, finding efficient communication strategies and compression techniques is key to optimizing the efficiency of FL implementation (Oh, Lee, Jeon, & Poor, 2021; Huang, Li, & Li, 2023).

In addition, there is a lack of uniform standardization in real-world implementations of FL. Different organizations may use different data formats, protocols, and architectures, which increases the difficulty of collaboration and the cost of implementation. The development and adoption of common standards is essential to facilitate the widespread adoption of FL technologies (Zhan, Li, Guo, & Qu, 2021). In this way, the creation of a federated learning with incentives facilitates data sharing between different organizations and enables the development of common standards. In the future, it may be possible to devise ways to punish malicious actors through incentive mechanisms.

Currently, there is no clear regulatory compliance framework for FL methods in the healthcare industry. This means that in order to achieve compliance, additional resources may need to be invested in developing and implementing complex compliance strategies, which is not only a cumbersome process, but can also be quite costly.

4 CONCLUSIONS

This paper comprehensively reviews the application of federated learning in pneumonia detection, especially the great potential it shows in processing sensitive medical data. By analyzing convolutional neural networks, ResNet50 and DenseNet121, the effectiveness of deep learning models has been demonstrated in improving the accuracy of pneumonia detection. In addition, this study explores how integration learning and federated learning, when used in combination, can effectively improve the generalization ability and data privacy protection of the models. Although federated learning has demonstrated many advantages in pneumonia detection, several key issues and challenges were identified, including data quality issues, communication overhead, changing healthcare regulations, and uniform standardization of federated learning. Future research could also explore how federated learning can be combined with other innovative technologies (e.g., quantum computing and blockchain) to further improve the efficiency and safety of pneumonia detection.

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