Paper Title:
Federated deep learning for detecting COVID-19 lung abnormalities in CT: a privacy-preserving multinational validation study
Paper Link:
https://www.nature.com/articles/s41746-021-00431-6

1 Summary
1.1 Motivation/purpose/aims/hypothesis: The study aimed to develop an AI model using federated learning for COVID-19 CT abnormality detection.The hypothesis was that federated learning could enhance the model's generalizability across multiple centers without sharing patient data which is crucial during a pandemic.

1.2 Contribution: This research demonstrates the feasibility of federated learning in a multicenter environment for COVID-19 image analysis. It highlights the effectiveness of decentralized training for developing AI tools while protecting patient privacy. The study's primary contribution is in showing the successful implementation of a privacy-preserving AI model for COVID-19 detection across diverse datasets.

1.3 Methodology: Authors collected datasets containing CT images, representing patients with confirmed COVID-19 infections from three local hospitals in Hong Kong. The Hounsfield units (HU) were clipped to ensure consistent intensity ranges across all volumes.Instance-level normalisation was done on dataset, which individually normalised each volume based on its statistics rather than using global dataset statistics.While implementing federated , each hospital acted as a local node, where individual models were trained. A central server facilitated the exchange of network parameters at regular intervals. The FedAvg algorithm was used to aggregate local models and update the global model. Transfer learning from the publicly available DeepLesion CT dataset was applied to mitigate data insufficiency. The deep convolutional network was fine-tuned with COVID-19 training images. Post-processing involved non-maximum suppression, a standard technique in image processing, to extract the bounding boxes with the highest predicted probabilities. Also, an open-source lung segmentation AI model was employed to remove false-positive detections outside the lung region.

1.4 Conclusion: The study confirms the effectiveness of the CNN-based AI model trained using a privacy-protecting federated learning approach. It exhibits wide generalizability across regional and international external cohorts, showcasing the promise of AI in providing scalable tools for lesion burden estimation.

2 Limitations
2.1 First Limitation/Critique: The first limitation of the study is the relatively small number of patients from each participating center. Although this multicenter approach was valuable, it resulted in an imbalance between centers in terms of the number of patients contributing to the study. This imbalance could impact the model's performance, especially in the context of COVID-19, where the number of cases at each center varied.

2.2 Second Limitation/Critique: The AI model showed reduced effectiveness on the German cohort, potentially due to demographic differences in the patient populations across different regions and differences in lesion annotation procedures. This challenge points out the need for standardized procedures in multicenter studies to ensure compatibility between datasets. Furthermore, it highlights the complexities of applying AI models to datasets with significant concept shifts.

3 Synthesis
Despite certain limitations regarding sample sizes and cross-center variations, the study holds promise for facilitating real-time clinical support and continuous patient monitoring using AI-based tools. The emphasis on federated learning as a solution for healthcare applications and the challenges posed by multi-center studies underscore the potential and future pathways of AI in healthcare.