State of the Art of Health Federated Learning: Lessons from a Systematic Review

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Key Messages

Need

Novel and heterogeneous research difficults evidence synthesis

Results

Increasing group of clinical domains and health data types being covered

Discussion

Assessments show attainable differences in comparison to traditional methods

Aim & Methods

We conducted a systematic review to find differences between decentralized learning methods for health data models and their non--decentralized alternatives (*i.e.*, local and centralized), with clinical applications. Several databases (ACM DL, IEEE, Lens, Lippincott Williams & Wilkins, Scopus, Springer, Web of Science, Wiley Online Library) and registers (arXiv, medrXiv, PROSPERO and Cochrane) were queried on April 6th and 7th 2023. Papers were screened by title and abstract and by their full text, by two researchers each in a blinded fashion. For this poster, we selected the preliminary results of only primary articles published in peer-reviewed scientific journals featuring federated learning.

Results

In total, 61 primary articles meeting the eligibility criteria were considered for this analysis. These comprise 173 federated learning models. COVID-19 was the most frequent analysed condition. Image-based data were the most common health data types used. Each model was compared with their respective local or centralized homologues.

Comparisons with local data approaches amounted to 155, and 194 comparisons with centralized data counterparts. Figure 3 showcases both types of comparisons regarding accuracy, ordered by the federated learning model's performance. Figures 4 and 5 present the distribution of the difference in performance of considered methodologies.

Fig. 1 - Articles by Groups of Conditions

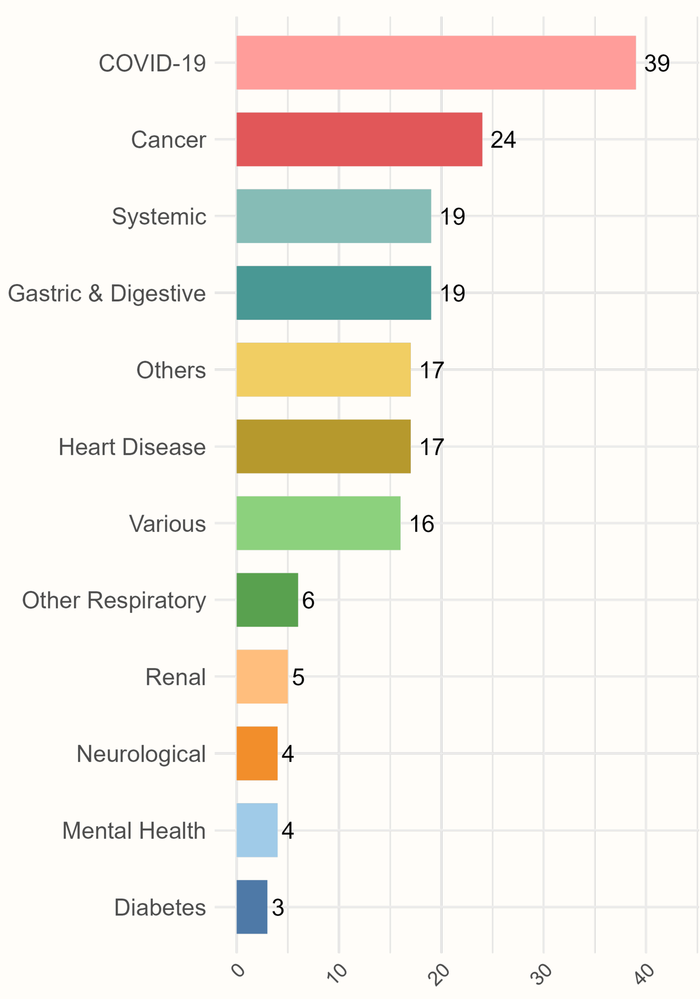


Fig. 2 - Articles by Type of Data Used

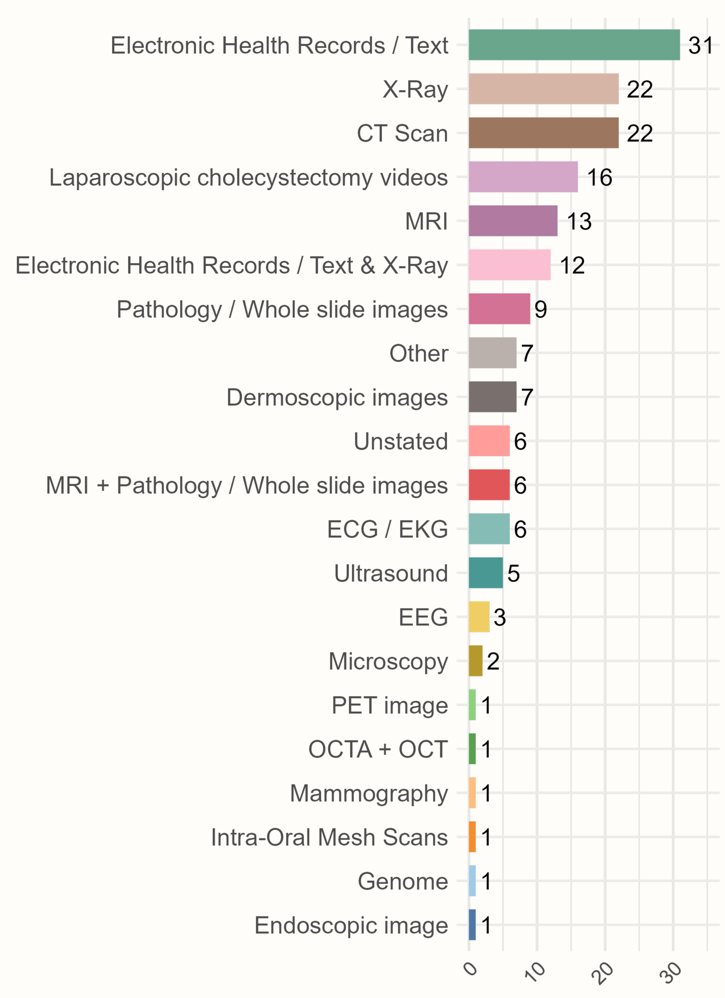


Fig. 3 - Model Performance Across Variants by Comparison

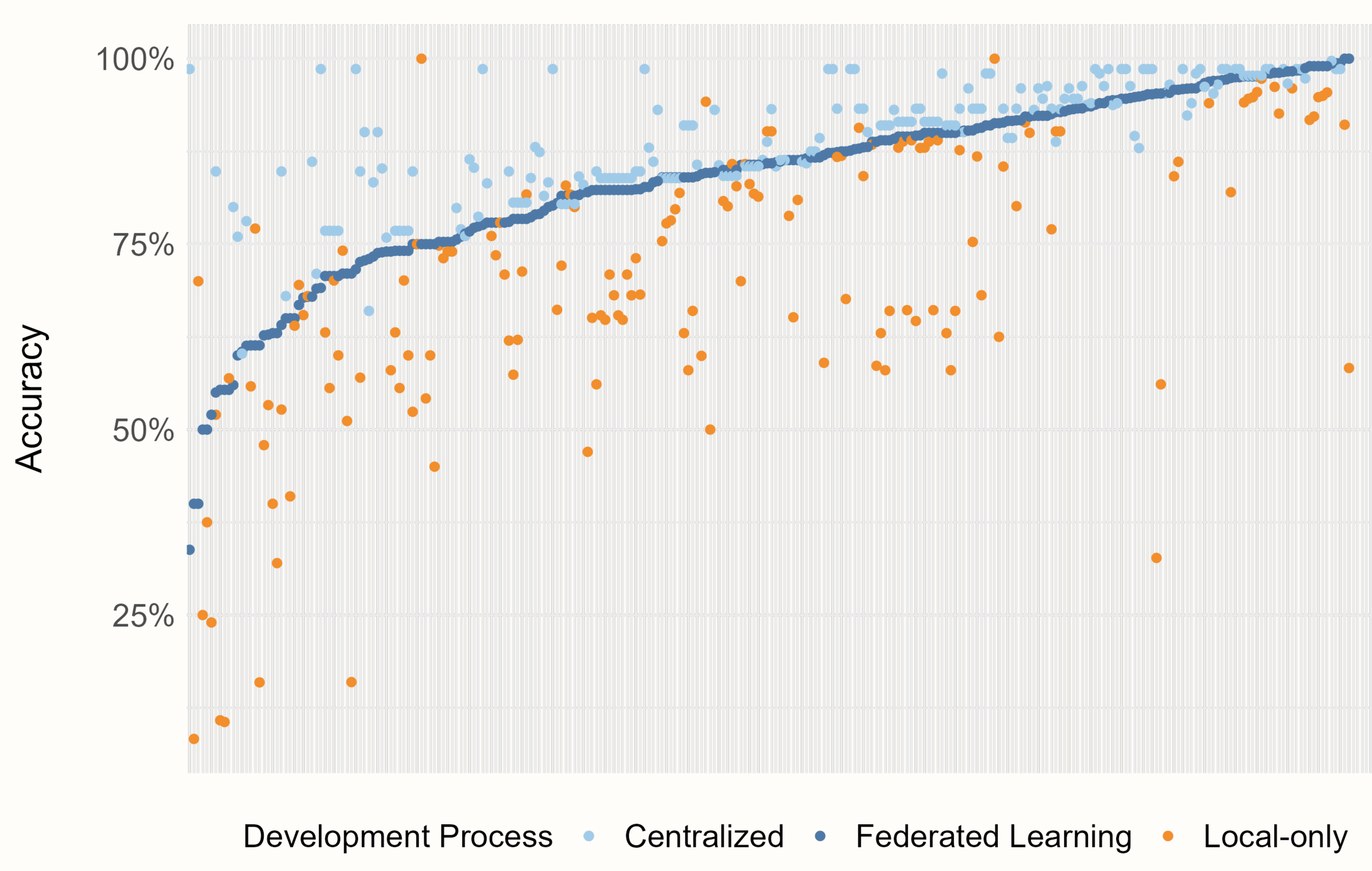


Fig. 4 - Model Performance Across Variants by Comparison

Federated Learning versus Local Learning: Superior in 88% of the comparisons

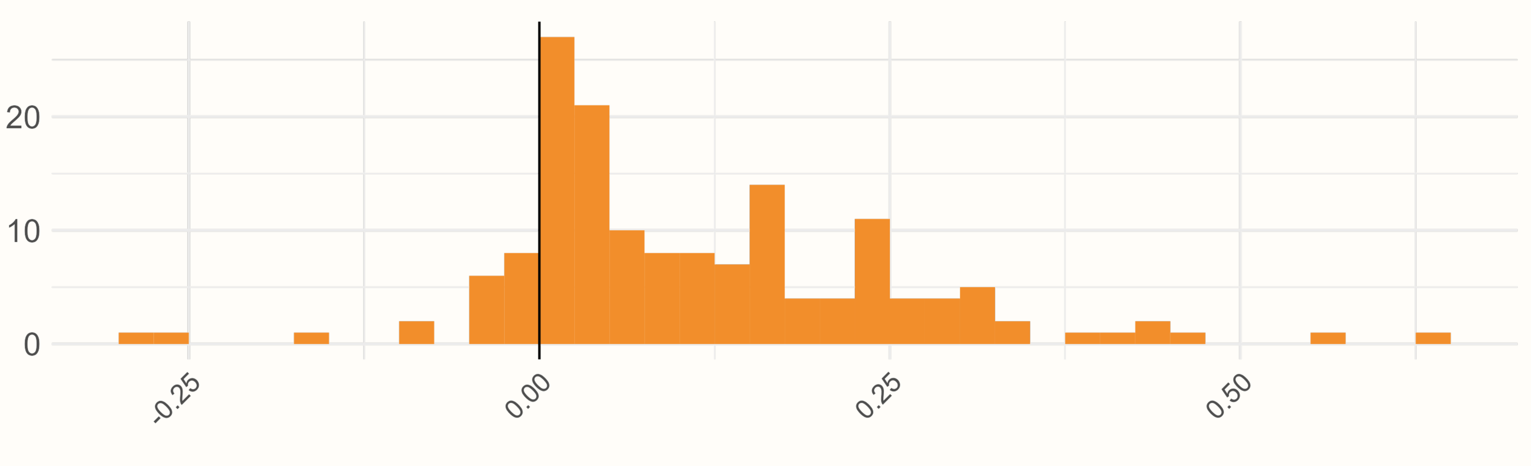
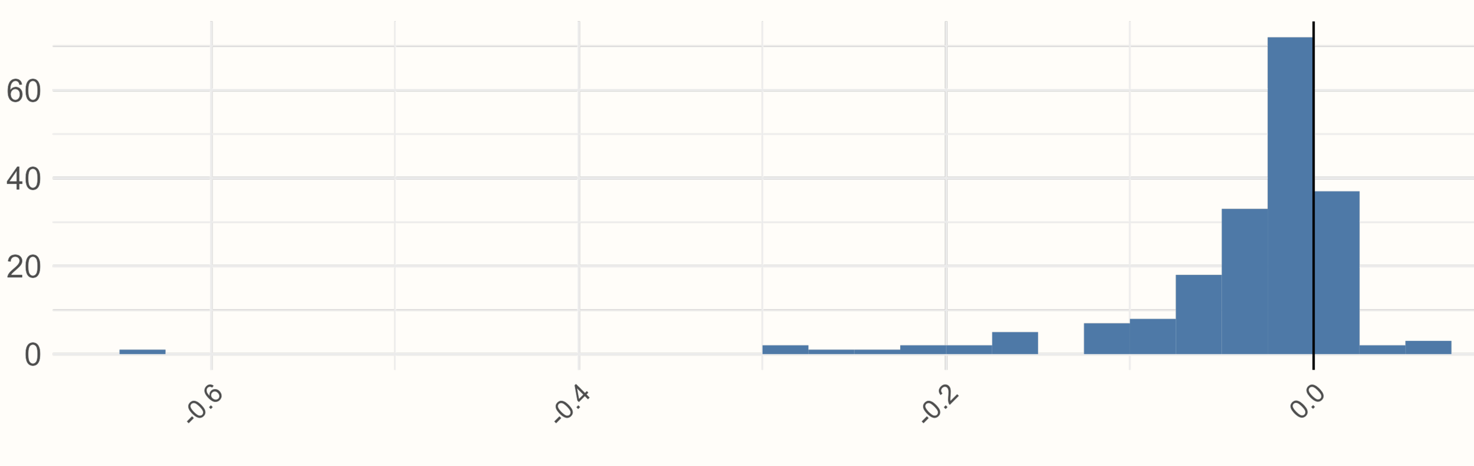


Fig. 5 - Model Performance Across Variants by Comparison

Federated Learning versus Centralized Learning: Superior in 22% of the comparisons



Discussion

Since 2016, there have the variety of the clinical applications and health data formats covered has increased in scope. These results showcase the robustness of Federated Learning approaches across several Machine Learning use cases. However, another trend in the available research mostly presents isolated implementations of these methodologies, with little continuity among papers of the same authors or using the same data or pipeline.

Moreover, there is much heterogeneity regarding the methods used and reporting practices. This further difficults the comparison and meta-analysis of any systematic literature review. The lack of assessment of clinically relevant or statistically significant differences of the models' performance hinders more rigorous appraisal of the data presented.

In the near future, it is expected that data harmonization and demanding technical and bureaucratic overheads will continue to be the main challenges for the field. At the same time, new directions should be considered, including preventive care, out-of-hospital data usage and deployment, as well as the design of real-time prospective studies.

We expect the final results to enlighten researchers and decisionmakers about the current viability of Health Federated Learning approaches. These are to be considered in the context of data protection legislation (*e.g.*, GDPR, HIPAA), the emergent trend of digital medical devices and the global health system crises and burden of disease.

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