Paper Title : The Future of digital health with federated learning
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1. Summary :

Machine learning has leveraged the availability of medical data by coming up with extraordinary results. It has yet to see its peak because most of the medical data are not available publicly due to privacy concerns. Federated learning is a technique where the model is sent to the user instead and ensures privacy. It also encourages the model to be trained on a diverse amount of data. Which yields more robust results.

Terms:

1.1 Motivation:

Without a sufficient amount of data, machine learning cannot meet its full potential. In order to achieve maximum results we need to ensure data safety to the users as well as provide a model with adequate amount of data so that it can train on a diverse amount of data to perform well. This is where the urge of using federated learning in the medical sector comes to play a role.

1.2 The contribution:

Medical data being trained on a particular institution yields biased results. Main reason is that the model is trained on a dataset which belongs to a particular population. As a result the model does well on that particular population. But whenever the model sees diverse data it underperforms. By using federated learning the authors show that people from different parts of the goal can participate in the model training. As a result the model won't be isolated to a particular population rather exposed to a diverse population. This paper shows the power of federate learning in the medical sector plus the possible challenges which might take place for implementing federated learning.

1.3 Methodology:

In order to perform federated learning on medical data , a data pool needs to be selected where diverse data from different institutes is available. Demographic data biases need to be taken care of. Anonymously controlling the access of data is challenging and sometimes impossible. By using genomic data and medical images, reidentification of a patient is also possible. In order to avoid that restriction can be applied and proper protocols should be implied. Moreover gated user access can be a solution for ensuring security. The model is then sent to the data for training. It has the advantage of ensuring security and storage cost minimization. In the decentralized method, the model is sent to data and the results aggregated on a central server. But it is often seen that models can also memorize data. To ensure privacy, learning from encrypted data has been proposed. Large medical institutions, pharmaceuticals who tend not to share data can collaborate using federated learning as well. Fed. Learning might impose a paradigm shift which will have its effect on different stakeholders. For example clinicians are usually exposed to a particular subgroup and they make decisions based on them. But fed learning is exposed to a wide array of scenarios. By accumulating knowledge from model and clinician predictions can be made.

1.4 Conclusion:

To sum up, by clarifying the revolutionary potential of federated learning in furthering the objectives of precision medicine, population health management, and medical research, "The Future of Digital Health with Federated Learning" significantly adds to the literature on healthcare informatics and machine learning. The paper is a significant resource for researchers, practitioners, policymakers, and stakeholders that aim to leverage federated learning to drive innovation and enhance healthcare delivery globally. It does this by offering a thorough analysis, insightful examples, and meaningful insights.

Limitations:

Federated learning is a convincing technology to use for data safety, diverse data availability and endless collaboration. But controlling remotely, ensuring security and creating protocol as both technically and computationally challenging. Obviously it will be hard to maintain as well.

A distribution system is always costly and hard to maintain. Moreover, finding out the problem or debugging the system is also challenging.

As every data is not of equal dimension or even distribution. It will be challenging for the model not to provide skewed predictions.

Synthesis:

The technical challenges are there. But with the rapid advancement of technology and Google's exceptional demonstration on the usage of federated learning inspire us to use this exciting technology in the medical domain to create robust models.